Jack Nicholson
I did not use data posted by the author
My substantive addition data are n/a

Replication of "Do State-Customized TANF Work Policies Actually Reduce Unemployment?"

Section I: INTRODUCTION

In Na Yeon Kim and Frances Stokes Berry's paper "Do State-Customized TANF Work Policies Actually Reduce Unemployment?", the researchers attempt to determine if the implementation of Worker Supplement Programs (WSPs) caused the unemployment rate of low-income females to decrease (Kim & Berry 2019). Using a difference-in-differences model, they find that states that enacted WSPs attained about 18 percent fewer unemployed low-income females when compared with states that did not implement WSPs. Through my replication process, I closely matched Kim and Berry's summary statistics, but the ambiguity of their data collection methods hindered my ability to exactly match their data. Additionally, I realized Kim and Berry likely excluded the use of fixed effects and time trend variables from their model, despite stating otherwise, calling into question the validity of their findings. When excluding fixed effects and trend variables, I find that states with WSPs had about 20 percent fewer unemployed low-income females. The inclusion of fixed effects and trend variables, however, caused the WSP variable to become about 0 percent and insignificant. Furthermore, I extended their research by using synthetic control methods (SCM) to analyze the implementation of specific WSPs in four states, which in general provided additional evidence that questions the validity of their findings. The rest of this paper contains the following chapters: II) Policy Background; III) Paper Background; IV) Data Collection; V) Summary Statistics; VI) Main Findings; VII) Synthetic Control Method; and VIII) Conclusions.

Section II: POLICY BACKGROUND

Following through on President Bill Clinton's promise to "end welfare as we know it," the federal government established the Temporary Assistance for Needy Families (TANF) block grant through the Personal Responsibility and Work Opportunity Reconciliation Act of 1996 (PRWORA) (Falk 2021). TANF succeeded the Aid to Families with Dependent Children (AFDC) program, a policy created through the Social Security Act of 1935 in which the federal government reimbursed states for cash assistance they provided to needy families (Falk 2021). PRWORA shifted the financing of welfare and broadened the options states had to use federal funding for welfare. Under TANF, the federal government issues a block grant to states, which, as long as they meet specific requirements (including allocating some of their own dollars), use these funds to operate state-specific programs to provide cash and other forms of assistance to needy families with children (Center on Budget and Policy Priorities, 2022). Under AFDC, states spent most of their funds on providing cash assistance to families, whereas about 20 percent of TANF funds went toward cash assistance in 2020 (Azevedo-McCaffrey & Safawi 2022).

In 2005, the federal government enacted the Deficit Reduction Act (DRA), which created stricter requirements on state TANF programs, including more stringent work requirements (Parrot et. al. 2007). Some states responded by creating WSPs, which provided former TANF recipients cash and noncash assistance with the aim of helping them maintain employment (Kim & Berry 2019). According to Kim and Berry, 19 states enacted some version of a WSP between 2005-2013. While Kim and Berry group these 19 states together as a treatment group, WSPs differ in size, scope, and methods.[1] Schott (2008) highlights some common differences of WSPs:

[1] Issues arising from these inconsistencies across states are explored further in chapters VI.

- **Cash Assistance**: Monthly cash assistance ranged from $10 in Michigan to the full TANF benefit in Utah. States also differ in whether benefits change over time (ex. benefits decreased throughout the program in Utah and Maine) or if recipients received bonus payments (ex. Arkansas awarded bonuses for meeting job retention targets).
- **Duration of Assistance**: States differed in whether WSP benefits counted against a recipient's limit on receiving TANF benefits. Additionally, state TANF policies had varying time limits.
- **Eligibility:** States varied on whether they issued an upper income limit on recipients in the WSP program. Furthermore, states differed on whether they automatically enrolled eligible participants versus mandating participants apply.

These categories only scratch the surface of the myriad differences in WSPs.[2] While WSP policies varied across states, they shared a common goal of increasing work participation rates of former TANF recipients, and in effect decreasing unemployment among targeted populations. Kim and Berry's paper attempts to determine whether WSPs caused unemployment rates to decrease.

Section III: PAPER BACKGROUND

Kim and Berry hypothesize that "States implementing worker supplement programs are more likely to achieve lower unemployment among low-income females than states without these programs" (913). Simply assessing the unemployment rate of states who implemented WSPs versus those who did not would not be a sound approach to test this hypothesis, given endogeneity concerns. The treatment (enacting a WSP) is not randomly assigned – states needed to choose to enact the policy – and states may have elected to implement (or not implement) an WSP at a given time due to a mix of factors, such as government ideology, total taxable resources, and other state characteristics.

[2] Other differences Schott (2008) highlights include, but are not limited to, funding used, additional enrollment policies, additional eligibility requirements, and connection with other benefits, such as Food Stamps/SNAP and Medicaid.

To account for endogeneity concerns, Kim and Berry used a difference-in-differences model for the 50 U.S. states from 2005-2013 to study the causal relationship between WSPs and unemployment rates of low-income females. A difference-in-differences model is a quasi-experimental design that uses panel data to highlight the differences in outcomes between a treatment group and a control, accounting for covariates. In its simplest form, this method uses four means (control before treatment, treatment before treatment, control after treatment, and treatment after treatment) to determine the effect of a treatment.

An essential element of a valid difference-in-differences model is evidence that the data satisfy the parallel trends assumption. The assumption is that the control and treatment groups should have the same pre-treatment trends, so that a shift in trends post treatment can be attributed to the treatment. Kim and Berry wrote in a footnote that they tested parallel trends by creating interaction terms for 2007 and 2008-2013 by "multiplying time dummies by treatment variable and [regressing] the same outcome variable on those interaction terms" (917). The coefficient of the pretreatment period (2006) was insignificant, which they said, "indicates that difference in differences between states in the treatment groups and control groups are not significantly different in the pretreatment periods" (917). As shown in Table 2, I replicate this process and confirm that the pretreatment variable (2006) was insignificant. I wonder, though, why they did not describe in greater detail this essential component of a difference-in-differences model. For example, they do not explain why years 2005 and 2007 were excluded. Table 3 shows the results for a regression that includes these two additional years, and the interaction terms for 2005 and 2006 (pre-treatment years) are insignificant, which passes their parallel trend test. Table 4, which provides annual descriptive statistics and t tests, shows the dependent variables for treatment and control states generally followed the same trend between 2005-2007. Chapter VI explores their specific model in greater detail.

Section IV: DATA COLLECTION

The unit of analysis in Kim and Berry's study is state year. Their dataset contains 450 observations, implying they did not exclude any observations. Table 1 details for each variable the data Kim and Berry, the data I used, whether I replicated their findings, and challenges I faced when attempting to replicate the data for each variable.

Kim and Berry's dependent variable is "the logged number of unemployed females whose income is below the federal poverty level" (915). They write that "the data are available on the U.S. Census," but they do not specify which specific data they used (915-916). I used American Community Survey (ACS) 5-year estimates for years 2005-2009 and ACS 1-year estimates for years 2010-2013 to construct the dependent variable (American Community Survey 2022).[3] Given that ACS provides these data in absolute terms, I found the rate by dividing the number by each state's population, obtained via the Census Bureau's State Intercensal Tables for 2005-2009 (2021) and from the State Population Totals and Components of Change Tables for 2010-2013 (2021). I then took the natural log of each rate.[4] The researchers did not specify where they acquired state population data, as well.

The primary independent variable is an indicator for WSP, in which each state year is coded 1 for the years it had a WSP and 0 otherwise. The researchers write that they obtained the data from a variety of sources paired with their own research into these programs. Kim and Berry

[3] I obtained the data within each dataset from variable B17005 (Poverty status in the past 12 months of individuals by sex by employment status)

[4] Throughout this project Census data were received either from the U.S. Census Bureau or from IPUMS' National Historical Geographic Information System (National Historical n.d.)

include the states that had WSPs in their appendix. WSPs, however, rarely begin at the start of the calendar year – several begin as late as October – and the researchers do not specify how they determine which years should be coded 1 versus 0 in these situations. I coded any year in which a policy was at least partially in effect as 1. Additionally, they do not specify how they code South Dakota, given they can't find an implementation date. They write in the appendix that South Dakota had "implemented transitional employment allowance program since 1997," leaving me to assume it should be labeled as 1 for all years.

Kim and Berry included 11 additional covariates. Three of the variables – sanction effect on SNAP (Supplemental Nutrition Assistance Program), full family sanction, and shorter lifetime limit – are indicator variables that deal directly with state TANF regulations. The variables are defined as follows:

- **Sanction Effect on SNAP**: policies that bar TANF recipients from also receiving SNAP benefits.
- **Full Family Sanction**: Policies that sanction all members of a family from receiving TANF benefits when one member does not meet a work requirement.
- **Shorter Lifetime Limit:** When states "adopt shorter lifetime limits than the federal lifetime limit of 60 months" (p. 916).

These variables are coded 1 if the state includes the regulation described. Data for sanction effect on SNAP comes from Table 1 in the paper's appendix. The authors acquired data from the Urban Institute's Welfare Rules Database for full family sanction and shorter lifetime limit. Beyond saying these data came from this database, the authors do not explain which data they used for these variables, which would have been helpful given the database's extensive data. Using the Welfare Rules Database, I coded full family sanction units 1 if the as_worst[5] variable from the Activities Sanctions dataset described a scenario where the full family would be sanctioned from

[5] "Describes the worst case sanction for non-compliance with an Activities Requirement" (Activities Sanctions n.d.)

receiving TANF benefits in response to a violation. I coded shorter lifetime limits units 1 if their tl_lamos[6] variable for the Time Limits dataset was less than 60 months.

Kim and Berry include six covariates that address state economic and welfare policies: state Earned Income Tax Credit (EITC) rate, unemployment rates, logged weekly benefits of unemployment insurance, actual duration of unemployment insurance, and total taxable resources per capita. The researchers said they acquired EITC[7] data from the Center on Budget and Policy Priorities, but they do not cite where specifically they retrieved the data. Because I could not find the source they used, I included data from the National Bureau of Economic Research (Shapiro n.d.). The researchers used data from U.S. Bureau of Labor Statistics (BLS) for unemployment rate, and I pulled BLS data from using Iowa State's Iowa Community Indicator Program, which perfectly matched the summary statistics from the paper (Annual Unemployment Rates n.d.). For logged weekly benefits of unemployment insurance and actual duration of unemployment insurance, Kim and Berry say they used data from the U.S. Department of Labor (DOL), but they do not specifically say where they retrieved the data. I pulled data from DOL's Unemployment Insurance Data dataset (Unemployment Insurance Data 2022). Finally, the author's and I both used data from the U.S. Department of Treasury to measure total taxable resources, but once again they did not cite specifically where on the Treasury's website they acquired these data (Total Taxable Resources n.d.).

Finally, three additional state characteristic variables used include the ratio of nonwhite citizens, the logged ratio of low-income females whose education level is at or below high

[6] "Describes the maximum number of months an assistance unit is eligible for benefits for the Group described in Lifetime Limit A" (Time Limits n.d.)

[7] States have the option to issue taxpayers an additional portion of the federal EITC. For example, if a state's EITC rate is 20 percent, a taxpayer who receives a $100 EITC credit from the federal government would receive an additional $20 credit from the state.

school, and state government ideology. The researchers said they used data from the Census for both the ratio of nonwhite citizens variable and the logged ratio of low-income female education variable, but they did not specify which specific data from the Census they used. For ratio of nonwhite citizens, I used the Census Bureau's State Intercensal Tables for 2005-2009 (2021) and State Population by Characteristics dataset for 2010-2013 (2021). I used ACS 5-year estimates for years 2005-2009 and ACS 1-year estimates for years 2010-2013 for the logged ratio of low-income females whose education level is at or below high school variable (American Community Survey 2022).[8] Kim and Berry used a variable developed by Berry et al. (2010) to measure the government ideology of each unit's government on a 0-1 scale, in which a higher score equates to a more liberal orientation. They don't specify how they assembled the dataset for each unit, and I applied the dataset Fording (2018) created using Berry's (2010) variable.

Kim and Berry's failure to clearly describe the data used made accurately replicating this paper more laborious than it needed to be. Additionally, the lack of description of the data used could make one question the validity of their results. If one cannot follow the data collection process they used, how can one in full confidence accept the results? Kim and Berry's paper would be stronger if they made clear how they assembled their dataset.

Section V: SUMMARY STATISTICS

Table 5 in the appendix copies the summary statistics from Kim and Berry's paper[9] and includes my attempt at replicating their descriptive statistics. Kim and Berry included the mean, standard deviation, minimum, and maximum for each variable. Of the 13 variables, I perfectly

[8] I obtained the data within each dataset from variable B17003 (Poverty Status in the Past 12 Months of Individuals by Sex by Educational Attainment). I created rates by dividing by state population, then took the natural log for each unit.
[9] Table A2 in their appendix

match one variable. When excluding the eight minimums and maximums of indicator variable, I match 9 of the 31 individual values.

Despite the inability to identically match many of their statistics, most of my descriptive statistics were close to Kim and Berry's results.[10] Of the 13 replicated means, one identically matches, eight are within 0.1 of the original results, and four are greater than 0.1 different from the original results. Of the 13 replicated standard deviations, one identically matches, 10 are within 0.1 of the original results, and two are greater than 0.1 different from the original results. The variable that most concerns me is the dependent variable, logged per capita unemployed females with low incomes. Despite similar minimums, maximums, and standard deviations, the mean of the original (-5.191) is more than 0.4 smaller from the replicated results (-4.779).

The failure to exactly match the results did not surprise me, because as I described in detail in Chapter IV, Kim and Berry rarely specified how they retrieved their data. Too often, they cited a broad source (ex. Census, DOL, etc.) without explicitly documenting which data they used. They also did not describe how they built their variables when additional work was needed, such as creating proportions and calculating logs. Most fascinating (and worrisome) to me is the inability to match the WSP variable, an indicator with data provided in their paper.[11] I believe lack of clarity in their coding process code be the issue for failing to exactly match their WSP variable. While not ideal, these findings are close enough to expect at least similar findings.

[10] I color coded Table 4 to reflect this: For my descriptive statistics, results in black identically match with the original results, results in orange are within 0.1 of the original results, and results in red are greater than 0.1 different than the original results.

[11] Table A6 in their appendix

Section VI: MAIN FINDINGS

The equation Kim & Berry cite as their primary model (917) is:

$$\log y_{s,t} = \alpha + \beta X_{s,t} + \mu_s + \theta_t + \lambda_{s,t} + \varepsilon_{s,t}$$

Subscript *s* and *t* are for states and time, respectively. The *y* is unemployed females whose income is below the federal poverty level. *X* represents the worker supplement program and the 11 additional covariates. The variable of interest is the coefficient of the WSP variable, which the authors said showed the difference in outcomes between treatment and control states. μ_s and θ_t represent state and year fixed effects, respectively. They also include a state-specific time trend ($\lambda_{s,t}$) to control for time-varying unobserved effects.

After running several versions of Kim and Berry's model, I discovered that they likely did not use this exact model to produce their primary results, despite saying otherwise. They report that their primary findings, significant at the 1 percent level, are that "States implementing worker supplement programs tend to have approximately 18 percent fewer unemployed low-income females than states that did not implement worker supplement programs, holding other variables in the model constant" (917). Using my dataset, which closely resembles Kim and Berry's, and the exact model described above, I found states with WSPs had about 0.5 percent more unemployed low-income females, holding all else constant, and this value was not significant. When I removed the time trend variables,[12] I found that states with WSPs had about 6.4 percent fewer unemployed low-income females, holding all else constant. This finding, which was significant at the 5 percent level, was more in line with Kim and Berry's results, though still three times smaller than their main finding. When I also remove state and year fixed

[12] $\log y_{s,t} = \alpha + \beta X_{s,t} + \mu_s + \theta_{,t} + \varepsilon_{s,t}$

effects,[13] however, the findings more closely match. This model shows that states with WSPs had about 20 percent fewer unemployed low-income females, a finding that, like Kim and Berry's results, was significant at the 1 percent level. Additionally, results for most covariates, while not perfect, most closely match the model without fixed effects and trend variables when compared with the two other models. Table 6 includes Kim and Berry's original results and my results for the three models described here.

Kim and Berry's results are misleading, given that it appears they said they used one model but apparently reported findings from another. An error this large should cause readers to question the paper's results. In a larger sense, my findings also demonstrate the importance of fact-checking work and the value of replication projects.

Section VII: SYNTHETIC CONTROL METHOD

In addition to my attempted replication of Kim and Berry's paper, I further investigate their causal claim by using synthetic control methods (SCM) to test their causal question on state-specific programs. Athey and Imbens (2017), who call SCM "arguably the most important innovation in the policy evaluation literature in the last 15 years," emphasize how the method "builds on difference-in-differences estimation, but uses systematically more attractive comparisons" (9). As Abadie (2021) describes, SCM, which he and Gardeazabal (2003) created, has been used to estimate the effects of interventions "implemented at an aggregate level affecting a small number of large units (such as a cities, regions, or countries), on some aggregate outcome of interest" (392). This description matches the state-specific nature of WSPs and the question as to whether they cause unemployment to decrease. Unlike a difference-in-

[13] $\log y_{s,t} = \alpha + \beta X_{s,t} + \varepsilon_{s,t}$

differences method, SCMs create a weighted control from a donor pool of untreated observations to create a synthetic counterfactual of the treatment. For example, if one was testing an impact of new policy in California, she would use selected covariates to create a synthetic California using portions of other states to predict how California would have trended had the policy not been implemented. In theory and when done correctly, the difference between the treatment and the control is the effect attributed to the treatment.

One could reasonably contend that for the casual question at hand, a SCM is an adequate alternative (if not the preferred method) to a difference-in-differences method, because the individual programs fit Abadie's description and differ across states. Additionally, as described more extensively in chapter II, Schott (2008) detailed differences in programs, such as size of cash benefit, duration of cash benefit, and eligibility and enrollment policies. Given the differences of the policies, one could reasonably contend that considering them each as equal versions of treatment could bias the outcome. What if, for example, more generous states see decreases in unemployment, whereas less generous states do not? On the flipside, what if there are no meaningful differences among programs that differ in terms of generosity? I scratch the surface of these questions using SCMs.

I use SCMs for Utah, Michigan, Pennsylvania, and Kansas to further explore whether a causal relationship exists between WSPs and unemployment rates of low-income females. I selected Utah and Michigan as the primary comparison, because they each launched their programs at the same time (February 2007), and their cash benefits greatly differ; Utah gave families the full TANF benefit whereas Michigan awarded families $10 per month (Schott, 2008). Table 7 compares the two programs in greater detail.

I use Stata's synth package to run the SCMs (Hainmueller n.d.). To maintain consistency with Kim and Berry's paper, I include the same set of covariates to create the synthetic controls. The donor pool consists of the 31 control states did not implement WSPs. Table 9 shows which states were used to create the synthetic control for each treatment state, and Table 10 compares the statistics of covariates of the treatment and synthetic controls for each state.

I anticipated the tests would show the treatment states had lower rates of unemployment than the synthetic controls and the gap would have been greater for Utah. The tests, however, produced different results. As Graph 1 illustrates, Utah's control generally matches the pre-treatment, but the synthetic control actually had greater predicted decreases in unemployment than the treatment. As for Michigan, depicted in Graph 2, the synthetic control does not match the treatment well, making it nearly impossible to draw any meaningful conclusions from this model.

Curious as to whether the limited pre-treatment data from only 2005 and 2006 could be to blame for the results, I analyzed Pennsylvania and Kansas, two states that launched their programs in 2009. Table 8 provides comparisons of Pennsylvania and Kansas' programs. I used the same methods for Pennsylvania and Kansas that I did for Utah and Michigan. The synthetic controls closely match the pre-treatment periods for both Pennsylvania and Kansas. After treatment, Pennsylvania saw slightly less unemployment than its synthetic control, whereas Kansas initially had slightly more unemployment than the synthetic control. Neither state's gap is large enough to draw meaningful conclusions on the WSP's impact on rates of unemployment among low-income females.

These SCM analyses only scratch the surface of how the method could be used to assess the causal question at hand. For example, fifteen treatment states were not included that could have been. Additionally, more pre-treatment data could have helped create better synthetic controls, which could have provided more meaningful results. Nonetheless, these findings add additional evidence that question Kim and Berry's findings. Although Kim and Berry reported a significant relationship between WSPs and unemployment of low-income females, the vagueness of their data collection, seemingly major inconsistencies in their methods and findings, and different conclusions found in my analysis make accepting their results challenging. While the results of my SCM analysis should not be viewed as definitive, conclusive findings, they offer more evidence to question the causal relationship Kim and Berry reported.

Section VIII: CONCLUSION

Kim and Berry attempted to provide much-needed research on a specific component of the United States' welfare system. Given the objectives of TANF, using WSPs to help former recipients maintain employment once they've exited the program is an aligned, meaningful goal. More broadly, this paper also attempts to add research to means-tested cash assistance policies. At first glance, their results, both large and significant, provide evidence that this policy benefits recipients and achieves its goal.

Their research, however, misses the mark in several important areas. First, the paper does not clearly describe the data collection and research methods used. The researchers vaguely describe their data, making it extremely difficult to determine the specific data they used. This problem could have been mitigated if the researchers made the data accessible, as they said they would,[14] but when contacted, they did not provide the data. Additionally, the researchers do not adequately describe their methods. They only briefly address the parallel trends assumption, an

[14] In the subhead of the online version of their paper, the authors write "The author will share all data and coding for replication purposes." I connected with Berry, who said she asked Kim for the data but that she never heard back.

essential component of the difference-in-differences method, and the equation they highlight lumps all variables together, making it difficult to visualize their difference-in-differences model.

Most importantly, the researchers appear to report misleading results. They state that they use state and year fixed effects and time trend variables, but the model I used that mostly closely matches their findings excludes fixed effects and trend variables. When including fixed effects and trend variables, the coefficient of interest is almost 0 and insignificant. This oversight caused me to greatly question their original findings.

This replication project accomplishes two main items: 1) questioning the original findings of WSPs and 2) demonstrating the need for careful documentation and fact-checking when writing and reviewing an econometrics paper. In addition to providing evidence that the significant decrease in unemployment among low-income females likely is not present using the methods the researchers describe, my use of SCMs offer additional evidence that questions the causality of this relationship. More importantly to econometrics research, this project highlights the importance for careful, well-documented research by illuminating crucial oversights in this paper. The researchers attempted to assess the causality of an important policy issue, but these errors ultimately limit the paper’s credibility.

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Appendix

Table 1: Variable Description and Replication Status				
Variable	Matched?	Data description from Kim and Berry.	My Data Source	Challenges
Logged per capita unemployed females with low incomes	Sort of Close	“The data are available on the U.S. Census Bureau website”	(American Community Survey 2022)	Don’t know which data they’ve used; have only found averages for 2005-2009, not annual data
Worker Supplement Program	Close	Used two reports and checked state TANF policy manuals	Table A6 (Kim & Berry 2019)	I was able to match when excluding one state, not sure if they did this
Full family sanction	Close	“Obtained from the Welfare Rules Database of the Urban Institute”	(Welfare Rules Database n.d.)	They do not say which variables they used from WRD
Sanction effect on SNAP	Close	Collected from 50 states’ policy manuals, administrative rules, and state plans.	Table A1 (Kim & Berry 2019)	Although provided in table, don’t make clear how they code certain states
Shorter lifetime limit	Close	“Obtained from the Welfare Rules Database of the Urban Institute”	(Welfare Rules Database n.d.)	They do not say which variables they used from WRD
State EITC rate	Close	“Information…is from the CBPP”	(Shapiro n.d.)	Not sure where their data is from
Logged weekly benefits of UI	Close	Obtained from Department of Labor website.	(Unemployment Insurance Data 2022)	Don’t know which DOL data they used
Actual duration of UI (weeks)	Close	Obtained from Department of Labor website.	(Unemployment Insurance Data 2022)	Don’t know which DOL data they used
Logged per capita females with at or below high school degree	Sort of close	“Data… are from the U.S. Census Bureau.”	(American Community Survey 2022)	Don’t know which data they’ve used. Have not been able to acquire these data yet.
Unemployment	Close	U.S. Bureau of Labor Statistics	(Annual Unemployment Rates n.d)	N/A
Non-white	Sort of close	“Data… are from the U.S. Census Bureau.”	(State Intercensal Tables 2021) and (State Population 2021)	Don’t know which data they’ve used
Government ideology	Sort of close	The government ideology variable developed by Berry et al. (2010)	(Fording 2018)	Not sure how they scored states
Logged TTS per capita	Yes	obtained from the U.S. Treasury website	(Total Taxable Resources n.d.)	N/A

Table 2: Parallel Trends Test Part 1				
Interaction Variable Years	Coefficient	SE	t value	P stat
2006	-0.090	0.171	-0.530	0.600
2008	0.018	0.080	0.220	0.825
2009	0.013	0.073	0.180	0.860
2010	-0.306	0.073	-4.180	0.000
2011	-0.295	0.071	-4.140	0.000
2012	-0.440	0.073	-6.010	0.000
2013	-0.568	0.075	-7.530	0.000
NOTE: Following the same method as the paper, I multiplied time dummies by treatment variable to get the interaction variables, and I regressed y variable on those interaction terms.				

Table 3: Parallel Trends Test Part 2				
Interaction Variable Years	Coefficient	SE	t value	P stat
2005	-0.371	0.295	-1.250	0.210
2006	-0.090	0.171	-0.530	0.598
2007	0.022	0.095	0.230	0.820
2008	0.017	0.080	0.220	0.829
2009	0.012	0.073	0.170	0.865
2010	-0.306	0.073	-4.180	0.000
2011	-0.296	0.071	-4.140	0.000
2012	-0.441	0.073	-6.010	0.000
2013	-0.568	0.075	-7.530	0.000
NOTE: Same method as Table 2, but include 2005 and 2007				

Table 4: Annual Dependent Variable Summary Stats			
	Mean (Standard Deviation in Parenthesis)		
Year	Treatment (n=19)	Control (n=31)	T Test
2005	-4.66 (0.24)	-4.55 (0.19)	1.75
2006	-4.66 (0.24)	-4.56 (0.19)	1.74
2007	-4.67 (0.24)	-4.57 (0.19)	1.68
2008	-4.68 (0.24)	-4.58 (0.19)	1.62
2009	-4.69 (0.25)	-4.59 (0.19)	1.58
2010	-5.03 (0.24)	-4.90 (0.27)	1.76
2011	-5.01 (0.29)	-4.87 (0.32)	1.57
2012	-5.13 (0.35)	-4.93 (0.32)	2.06
2013	-5.23 (0.40)	-5.00 (0.29)	2.35
NOTE: The data is for the dependent variable logged number of unemployed females whose income is below the federal poverty level			

Table 5: Summary Statistics								
	Original Paper				**Replicated Paper**			
	Min	Max	Mean	SD	Min	Max	Mean	SD
Logged per capita unemployed females with low incomes	-6.347	-4.272	-5.191	0.383	-6.345	-4.197	-4.779	0.329
Worker Supplement Program	0	1	0.227	0.419	0	1	0.251	0.434
Full family sanction	0	1	0.896	0.306	0	1	0.889	0.317
Sanction effect on SNAP	0	1	0.324	0.469	0	1	0.340	0.474
Shorter lifetime limit	0	1	0.222	0.416	0	1	0.213	0.410
State EITC rate	0	0.33	0.064	0.098	0	0.32	0.055	0.090
Logged weekly benefits of UI	5.175	6.049	5.635	0.182	5.175	6.056	5.634	0.183
Actual duration of UI (weeks)	10.2	27.1	15.865	2.572	10.975	23.675	15.840	2.445
Logged per capita females with at or below high school degree	-4.455	-2.972	-3.686	0.302	-3.951	-2.557	-3.260	0.300
Unemployment	0.026	0.137	0.063	0.023	0.026	0.137	0.065	0.023
Non-white	0.034	0.754	0.217	0.126	0.035	0.679	0.186	0.116
Government ideology	0	92.451	49.125	26.883	13.482	93.248	52.946	15.904
Logged TTS per capita	10.494	11.423	10.952	0.198	10.494	11.423	10.952	0.198

NOTE: For the four columns to the right, black means I identically matched with the results, orange means my results are within 0.1 of the original results, and red means my results are greater than 0.1 different than the original results.

Table 6: Replicated Findings Table				
	Paper Results (No FE or Trend)	My Results (No FE or Trend)	My Results (With FE)	My Results (With FE and Trend)
Worker supplement program	−0.186∗∗∗ (0.036)	-0.203∗∗∗ (0.032)	-0.064∗∗ (0.027)	0.005 (0.026)
Full family sanction	−0.049 (0.035)	-0.028 (0.049)	-0.008 (0.077)	-0.024 (0.085)
Sanction effect on SNAP	−0.089 (0.077)	0.081∗∗ (0.032)	-2.451∗∗∗ (0.421)	-169.702∗∗∗ (49.613)
Shorter lifetime limit	−0.048 (0.033)	0.046 (0.037)	0.116∗ (0.068)	0.034 (0.084)
State EITC	−0.105 (0.237)	-0.154 (0.178)	0.106 (0.247)	0.180 (0.257)
Log of weekly benefits of UI	−0.690 (0.434)	-0.418∗∗∗ (0.092)	-0.756∗∗∗ (0.172)	-0.534∗ (0.222)
Actual duration of UI	0.010∗ (0.006)	-0.037∗∗∗ (0.007)	-0.004 (0.008)	0.008 (0.008)
Log of at or below high school education	0.403∗∗ (0.152)	0.203∗∗∗ (0.060)	-0.449∗∗∗ 0.171	0.051 (0.161)
Unemployment	−0.850 (1.890)	3.487∗∗∗ (0.796)	1.512 (1.014)	-0.875 (0.922)
Nonwhite	1.200 (1.754)	0.046 (0.123)	-9.560∗∗∗ (1.684)	-12.023∗∗∗ (2.939)
Government ideology	0.000 (0.001)	0.008∗∗∗ (0.001)	-0.002 (0.002)	0.002 (0.001)
Log (TTS per capita)	−2.142∗∗∗ (0.337)	0.104 (0.090)	-0.362∗ (0.215)	-0.226 (0.264)
R2	0.922	0.351	0.874	0.939
Observations	450	450	450	450
NOTE: ∗∗∗ p < 0.01; ∗∗p < 0.05; ∗p < 0.1. Standard errors are in parenthesis.				

Table 7: Utah and Michigan Comparisons		
	Utah	Michigan
Monthly Benefit	$474 for 2 months and $237 for 3rd month	$10 per month
Full family sanction	Had full-family sanction policy for failure to meet work requirements	Had full-family sanction policy for failure to meet work requirements
Sanction effect on SNAP	Disqualified TANF recipients from also receiving SNAP benefits for failure to meet work requirements	Disqualified TANF recipients from also receiving SNAP benefits for failure to meet work requirements
Shorter Lifetime Limit	Had a shorter lifetime limit than the federal limit	Had a shorter lifetime limit than the federal limit
Qualification	Employed families leaving TANF because of income	Employed families leaving TANF because of income
Amount of Work Required	30 hours per week	No minimum
Duration	3 months	6 months
NOTE: Data in this table came either from the dataset used for this paper or from Schott (2008)		

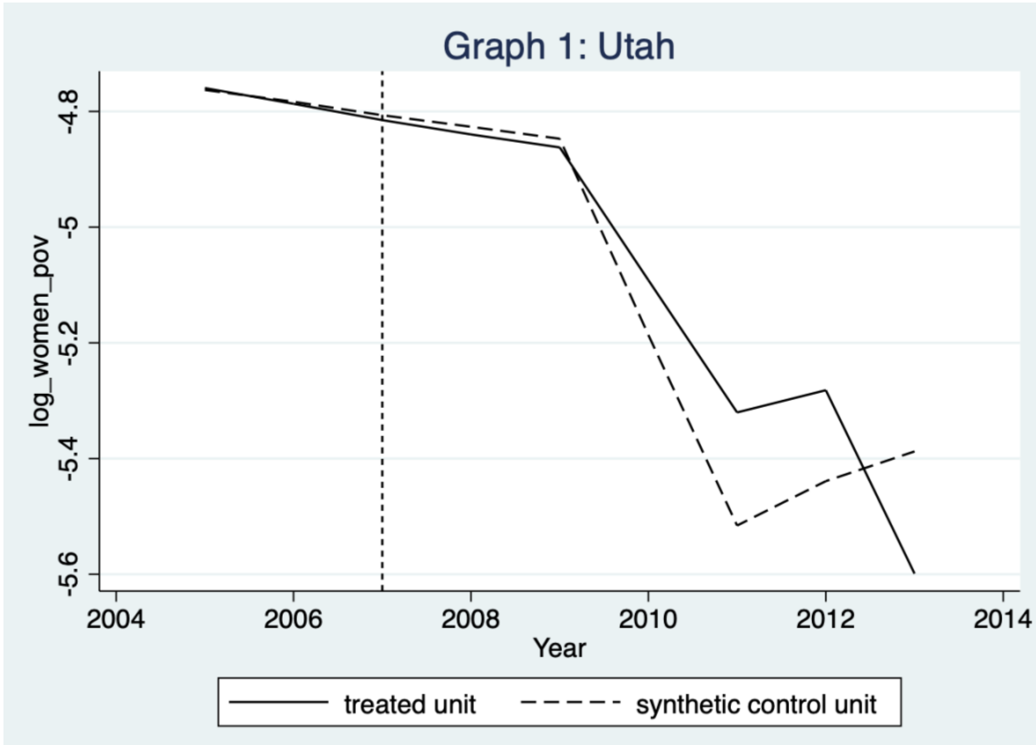
Table 8: Pennsylvania and Kansas Comparisons		
	Pennsylvania	Kansas
Monthly Benefit	$100 per month for three consecutive months	$50 per month for five consecutive months
Full family sanction	Had full-family sanction policy for failure to meet work requirements from 2011-2013	Had full-family sanction policy for failure to meet work requirements
Sanction effect on SNAP	No sanction on recipients' SNAP benefits for failure to meet work requirements	Disqualified TANF recipients from also receiving SNAP benefits for failure to meet work requirements
Shorter Lifetime Limit	Did not have a shorter lifetime limit than the federal limit	Only had shorter lifetime limit in 2012-2013
Qualification	"Certain families who are ineligible for continued assistance in the TANF, Extended TANF or Time-Out programs due to earned income"	Employed families leaving TANF because of income
Amount of Work Required	No minimum	No minimum
Duration	3 months	3 months followed by 12 months of work program transitional services
NOTE: Data in this table came from Kennedy and Blackwell (2008), Temporary Assistance for Needy Families Program (n.d.), or the dataset used for this paper		

Table 9: Synthetic Control Weights for Each State				
State	Utah	Michigan	Pennsylvania	Kansas
Alabama	0	0	0	0
Alaska	0.008	0	0	0
Arizona	0	0	0	0
California	0	0	0.001	0
Colorado	0	0	0.06	0
Connecticut	0	0	0	0
Delaware	0	0	0	0
Florida	0	0	0	0
Georgia	0	0	0	0
Hawaii	0.009	0	0.129	0.02
Idaho	0.349	0	0	0.007
Illinois	0	0.635	0.213	0
Iowa	0	0	0	0.478
Kentucky	0	0	0	0.231
Louisiana	0	0	0	0
Maryland	0	0	0	0
Mississippi	0	0	0	0
Montana	0	0	0.192	0.089
Nevada	0	0	0	0
New Jersey	0	0	0.131	0.147
New York	0	0	0	0
North Carolina	0	0	0	0
Ohio	0	0	0.273	0
Oklahoma	0	0	0	0
Rhode Island	0	0.066	0	0
South Carolina	0	0.299	0	0.007
Tennessee	0	0	0	0
Texas	0	0	0	0
West Virginia	0	0	0	0
Wisconsin	0	0	0	0.022
Wyoming	0.634	0	0	0
NOTE: States listed only include the 31 control states in the donor pool				

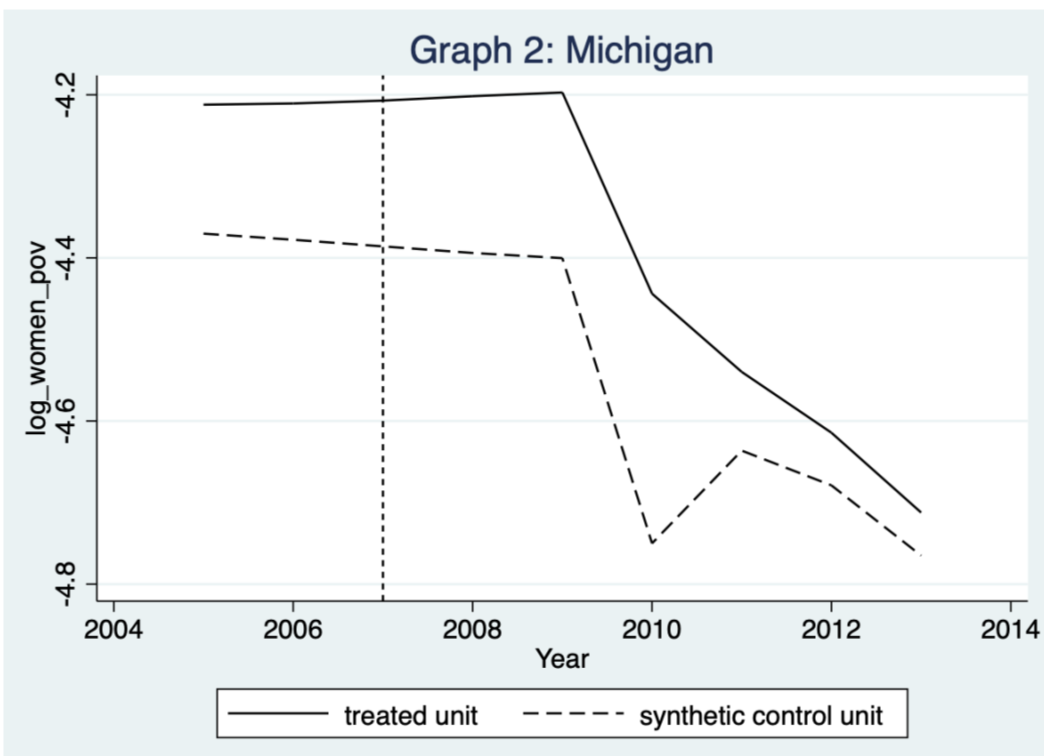
Table 10: Treatment and Synthetic Control Matching by State

	Utah		Michigan		Pennsylvania		Kansas	
Variable	**Treat**	**Syth**	**Treat**	**Syth**	**Treat**	**Syth**	**Treat**	**Syth**
Full family sanction	1.000	1.000	1.000	1.000	0.000	0.998	1.000	1.001
Sanction effect on SNAP	1.000	0.349	1.000	0.934	0.000	0.213	1.000	0.014
Shorter lifetime limit	1.000	0.349	1.000	0.066	0.000	0.000	0.000	0.007
State EITC	0.000	0.000	0.000	0.048	0.000	0.038	0.160	0.031
Log of weekly benefits of UI	5.595	5.498	5.676	5.591	5.744	5.681	5.688	5.666
Actual duration of UI	13.488	12.125	14.400	16.631	16.481	15.759	14.650	13.912
Log of at or below hs ed	-3.726	-3.600	-3.190	-3.176	-3.183	-3.365	-3.440	-3.334
Unemployment	0.036	0.035	0.069	0.055	0.048	0.048	0.046	0.046
Nonwhite	0.068	0.063	0.186	0.232	0.145	0.226	0.110	0.111
Government ideology	29.584	31.080	57.967	57.519	64.611	62.466	41.082	54.662
Log (TTS per capita)	10.774	10.990	10.818	10.908	10.925	10.920	10.876	10.887

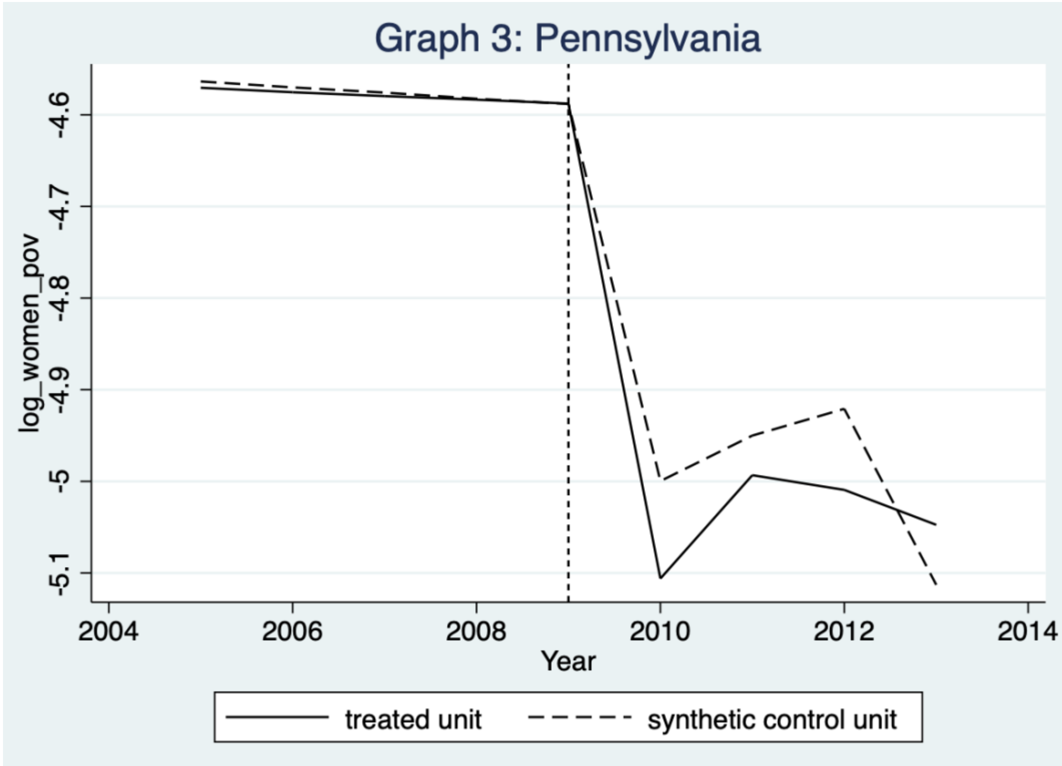
NOTE: "Treat" equals the treatment state and "Synth" equals the synthetic control. Color code used to separate the four states.

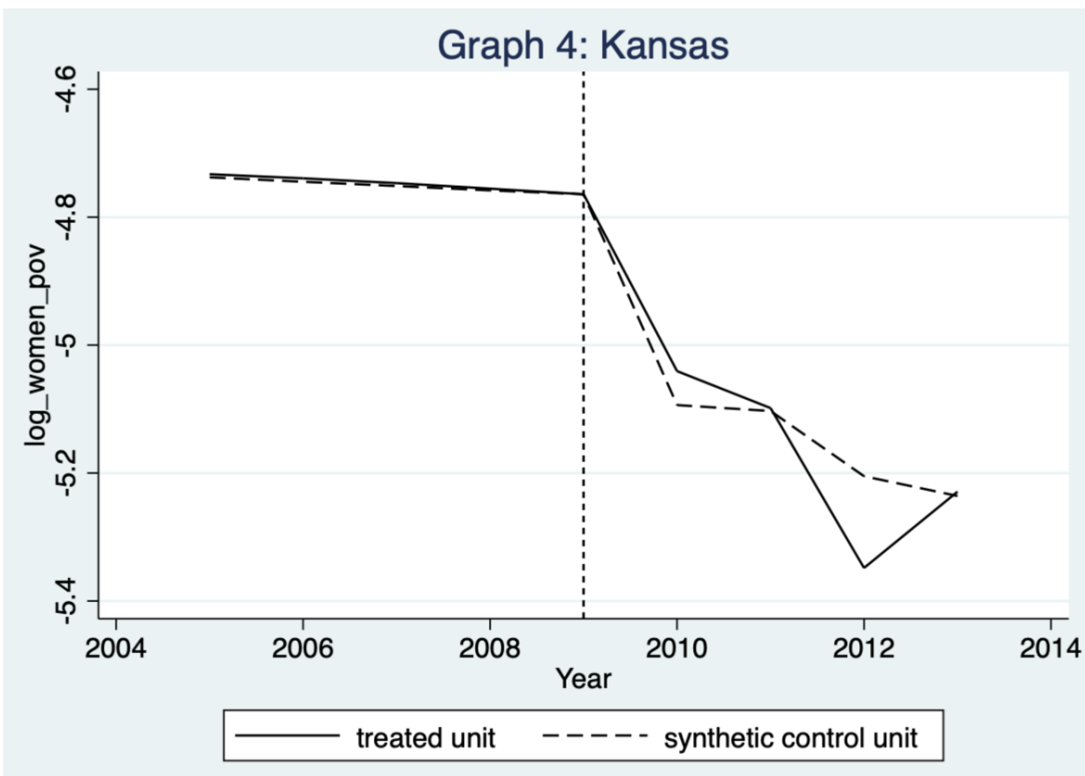


Graph 1: Utah
log_women_pov
-4.8
-5
-5.2
-5.4
-5.6
2004
2006
2008
2010
2012
2014
Year
treated unit
synthetic control unit



Graph 2: Michigan
log_women_pov
-4.2
-4.4
-4.6
-4.8
2004
2006
2008
2010
2012
2014
Year
treated unit
synthetic control unit


Graph 3: Pennsylvania
log_women_pov
-4.6
-4.7
-4.8
-4.9
-5
-5.1
2004
2006
2008
2010
2012
2014
Year
treated unit
synthetic control unit


Graph 4: Kansas
log_women_pov
-4.6
-4.8
-5
-5.2
-5.4
2004
2006
2008
2010
2012
2014
Year
treated unit
synthetic control unit