THE IMPACT OF WELFARE POLICY SHIFTS ON POVERTY AND WORK RATES

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ABSTRACT

The purpose of this analysis is to examine the impact of two aspects of the Temporary Assistance for Needy Families (TANF) policy: sanctions for noncompliance with work requirements, and magnitude of the welfare benefit. The current debate questions whether welfare benefits reduce employment among their recipients, and whether strict work requirements for these programs are necessary. Over the last decade, several states made significant changes to their TANF rules. This study examines Colorado, which significantly increased its maximum benefits over the span of one year, as well as Kansas, which strengthened its work requirements and sanctions. Synthetic controls and difference-in-differences estimation take advantage of sudden policy changes in individual states, using them to create natural experiments. This analysis suggests that increasing welfare benefits reduces poverty but also reduces work participation, while increased sanctions appear to have no effect on poverty rates and an unclear effect on work participation.

BACKGROUND

Work-Related Sanctions

Work requirements are a pressing issue shaping modern welfare policy, with governmental and nongovernmental actors debating the merit of applying those requirements to Medicaid and affordable housing programs. A comprehensive analysis of past random assignment studies analyzing work requirements by the left-leaning Center on Budget and Policy Priorities found that, overall, work requirements did not result in long-term stable employment, and did not reduce poverty at the individual level (Pavetti, 2016). However, the full report on MDRC's National Evaluation of Welfare-to-Work Strategies, which also used random assignment, does note positive effects for employment-focused programs, although those effects did fade after two years (Freedman et al., 2000). Gains to employment and earnings were modest, but statistically significant for most of the programs studied (Freedman et al., 2000). One program, Portland, had especially strong outcomes to both employment and earnings, even after five years, likely due to the rigor of its welfare-to-work program, experienced staff, and strong economy (Freedman et al., 2000).

The MDRC study specifically discusses sanctions, quoted here:

> Sanctions or threat of sanctions may also encourage some enrollees to complete employment-related activities, thereby strengthening the program's "treatment" effect. (Program administrators often state that this is the primary goal of imposing sanctions.) Programs that impose sanctions frequently may also encourage enrollees to leave welfare sooner, perhaps by taking a job that they would not have otherwise accepted, or even to forgo welfare without employment (Freedman et. al, 2000, p. 44).

The results from the random-assignment studies carried out by MDRC did not show a clear relationship between level of sanctioning and participation in program activities, although they do note that programs with a moderate level of sanctions seemed to achieve the best results (Freeman et. al, 2000). The researchers find that programs with especially low levels of enforcement seem to yield low program participation (Freedman et. al, 2000). Work programs had mixed results on employment rates, with the outcomes varying greatly by site. For those still receiving AFDC benefits, the impact of being in the work program ranged from a 1.6 percentage point decrease in employment rates to a 2.7 percentage point increase in employment rates (average of positive 0.81). The impact on employment rates for those no longer on AFDC (leavers) ranged from a 0.7 percentage point decrease to a 9.3 percentage point increase (average of positive 3.29). Most programs had little to no effect on poverty (Freedman et. al, 2000).

A separate study conducted by the Urban Institute in 2006 using SIPP data found that "as the duration of the most severe sanction increases, mothers' deep poverty increases, although the effect is marginally statistically significant at the 10 percent level" (McKernan and Ratcliffe, 2006, p. 20) The magnitude of their finding was that increasing the length of the sanction from "one month" or "until compliance" to a permanent sanction increased deep poverty rate of mothers by 1.4 percentage points, or 15.9 percent (McKernan and Ratcliffe, 2006, p. 20).

Welfare Benefits

The debate over welfare benefits is fairly intuitive: more generous benefits raise the incomes of those who receive them, but some argue that high benefits also create a disincentive for work, discouraging recipients from becoming self-sufficient and permanently improving their financial position. High benefits could even lower earned income to such an extent that increasing benefits decreases total incomes. The Cato Institute claimed in 2013 that "the current welfare system provides such a high level of benefits that it acts as a disincentive for work" (Tanner and Hughes, 2013, p. 1). This analysis was criticized by the Center on Budget and Policy Priorities, who noted that welfare shouldn't discourage work, particularly because benefits are not immediately lost simply because an individual or family gains employment (Pavetti and Parrott, 2013).

The Urban Institute study cited in the section above found that "[a] $100 increase in states' monthly maximum benefit is found to reduce the deep poverty rate of children by 2.0 percentage points" (McKernan and Ratcliffe, 2006, p. 19). However, the same study found that "higher monthly welfare benefits lead to higher poverty rates", speculatively due to effects on labor supply and earned income, a finding in line with a paper by Gundersen and Ziliak (2004) (McKernan and Ratcliffe, 2006, p. 21). This is an important finding for state and federal policymakers, and merits an updated analysis.

Research Question and Hypotheses

The core research question of this paper is: what are the impacts of different welfare policies and regulations within the United States? More specifically:

Do harsher and/or permanent sanctions for noncompliance impact work participation among TANF recipients, and what is the consequence to poverty alleviation? and

Do higher maximum benefits help lift more families out of poverty, and what is the consequence to work participation?

There are four hypotheses:

Hypothesis 1: Implementing sanctions that retract benefits permanently will lead to higher work participation and higher earned income among recipients of cash assistance.

Hypothesis 2: Implementing sanctions that retract benefits permanently will increase poverty as more individuals are sanctioned or leave welfare without achieving stable employment.

Hypothesis 3: Higher maximum benefits will have a negative impact on employment and earnings due to a decreased incentive to secure non-TANF income.

Hypothesis 4: Higher maximum benefits will lead to decreased poverty rates as the higher benefits will raise more individuals above the poverty line.

DATA

This analysis makes use of American Community Survey microdata to create a traditional difference-in-differences regression model. This dataset is publicly available, includes individual-level survey response data, and allows for cross-tabulations and variable analysis that traditional ACS data would not allow for. The population of individuals receiving TANF assistance can be roughly identified using the "INCWELFR" variable, which identifies the amount of income an individual received from various public assistance programs. The model also includes the following variables: sex, age, race, health insurance, educational attainment, employment status, weeks worked in the past year, wage and salary income, and total income (including cash transfers) as a percentage of poverty.

The synthetic control portion of the analysis uses administrative data of work participation rates from the US Department of Health and Human Services (HHS. However, this data is only publicly available aggregated at the state level. The HHS data functions well for the synthetic control method, the design of which is well-suited to use states as the unit of analysis, and doesn't rely on standard deviations to make estimates and test significance.

Data on changes in welfare policy are sourced from the Urban Institute's Welfare Rules Database, which provides a comprehensive set of tables on state TANF policy which are published in July of each year.

Descriptive Statistics

A simple bivariate analysis can show the association between welfare policies and outcomes. This analysis is necessarily incomplete, however, because the assignment of sanction and benefit policies is endogenous. Other factors which are related to both welfare policy and employment/poverty, such as local economic conditions, political culture, and state budgetary health will bias the results. For example, states with low workforce participation due to a lack of job opportunities in the state may impose harsher

sanctions, drawing a false relationship between harsh sanctions and low work rates. Or a state experiencing generally high poverty may raise their welfare benefits, drawing a false relationship between high benefits and high poverty.

Table 1 shows a summary of sanction policies across 43 states and DC, and how their average outcomes differ. Certain states are not included because they do not have one consistent sanction or benefit policy. Averages are calculated without weighting for state population. Keeping in mind that these policies are assigned endogenously, there does not appear to be a clear trend between the length of the worst-case sanction, and outcomes related to employment or the poverty rate. This table shows that states with a permanent sanction have participation rates in work-related activities that are 4.5 percentage points lower than states that only sanction benefits until recipients are in compliance again. The summary data also shows that, on average, permanent sanction states have poverty rates that are 1.5 percentage points higher than states that sanction until compliance.

Table 1:

Length of Worst-Case Work-Related Sanction	Number of states	Percent of Work-Eligible Individuals Participating in Work-Related Activities	Average hours worked in unsubsidized employment among those participating	Average State Poverty rate	Average State Deep poverty rate (<.5 poverty)
Until Compliance	7	57.7%	24.63	9.15%	3.57%
1-3 Months	10	51.73%	25.00	9.77%	4.10%
6 Months	3	50.70%	25.33	12.10%	5.18%
12 Months	3	50.84%	28.57	11.53%	4.80%
Must Reapply	14	44.00%	25.49	9.87%	3.94%
Permanent	7	53.19%	25.04	10.65%	4.35%

The results of simple bivariate regressions using maximum welfare benefits as the independent variable are shown in Table 2 below. The effects on employment and earnings are not significant, which pushes back against Hypothesis 3, and the effects on poverty are significant and in the expected direction, which provides some support for Hypothesis 4. As stated previously, however, the potential for omitted bias and reverse causality is clear. The coefficient on the state poverty rate indicates that each additional dollar in maximum welfare benefits is associated with a poverty rate that is .11 percentage points lower. In other words, $100 additional dollars in maximum welfare benefits is associated with a poverty rate that is 1.1 percentage points lower, which is substantial, given that the national poverty rate was 13.5 percent based on 2015 Census estimates.

Table 2:

Dependent variable of Bivariate	Coefficient on Max Benefit	t-value
Percent of work-eligible TANF recipients participating in work-related activities	0.00019	1.26
Average weekly hours spent working in unsubsidized employment among work-participating TANF recipients	-.00383	-1.12
State poverty rate	-.00011	-6.29***
State deep poverty rate (<.5 poverty)	-.00005	-6.08***

METHODS: DIFFERENCE-IN-DIFFERENCES AND SYNTHETIC CONTROL ANALYSIS

One way to control for endogenous variation is to perform a difference-in-differences analysis comparing two similar groups, one that imposed a policy change, and one that did not. This type of analysis compares a treatment and a control group at two points in time: before the implementation of the treatment and after. Under the assumption that the two groups should follow similar trends absent any treatment, subtracting the second difference (pre and post for the control group) from the first difference (pre and post for the treatment group) determines a local average treatment effect. By comparing differences between a pre and post period, this method controls for global trends. For example, if poverty for all states went up over the study period, but the treatment state went up by less, it can be found that the treatment reduced poverty. Difference-in-differences makes the key assumption that, absent any policy differences, the trend in the control state is what would be expected in the treatment state. An important way to defend this assumption is to argue that trends in the outcome for the treatment and control group were similar before the forcing variable (the policy change).

The analysis that follows will examine policy changes in the states of Colorado and Kansas. In 2009, Colorado increased their maximum TANF benefit from $356 to $462. Kansas made several significant changes to its sanction policy for non-compliance with work requirements between 2011 and 2012. In 2011, the initial sanction for non-compliance was removal of the entire benefit until the recipient was in compliance. There was no difference between the initial sanction and the most severe (worst-case) sanction. In 2012, the initial sanction was hardened: the entire benefit would be removed for three months and the recipient had to be in compliance with requirements for two weeks for benefits to be returned. Also, a worst-case sanction was added wherein the recipient would be sanctioned for their entire benefit for 10 years. Kansas also began including upfront job requirements,

shorter time limits on receipt of assistance, and shorter work exemptions for parents of infants. A new analysis by the Center on Budget and Policy Priorities, which focused on families who left cash assistance in the years after the policy shift, found no increase in work rates for families leaving assistance, and increases in earnings that were not substantial enough to lift families out of poverty (Mitchell and Pavetti, 2018, p. 1). However, this study is descriptive in nature, and does not compare Kansas to a control.

For both states, synthetic controls are first used to analyze state-level TANF

administrative data from HHS. The purpose of the synthetic control method is to generate an artificial group which is equal in expectation to the treatment group. This method attempts to solve the assumption that the treatment and control group would have followed similar trends absent treatment. Data are entered on the outcome variable for each state, as well as some independent predictors, which in this case included state unemployment, median household income, and the percent of residents receiving cash assistance. The software builds a synthetic state by weighting data from the pool of remaining states. This synthetic state will match the treatment state on the outcome variable of interest (given the independent predictors) as closely as possible up to the year before the first year of treatment. The produced graph can then be evaluated to determine whether the treatment state diverged significantly from its synthetic control after the treatment year, and if it did so in the expected direction. If the treatment state diverges from its equal-in-expectation synthetic state, it would suggest that the policy change made a difference.

The next stage of the analysis is a more traditional difference-in-differences regression model using American Community Survey microdata. The theoretic model is as follows:

$$Outcome_i = \beta_0 + \beta_1 Treatment_i + \beta_2 Post_i + \beta_3 (Treatment * Post)_i + \beta_4 X_i + \varepsilon_i$$

Where "Treatment" is a flag for whether the state is the treatment state; "Post" is a flag for whether the year is after the year the policy went into effect; and the interaction between "Treatment" and "Post" yields the overall impact of the policy, i.e. the difference in differences. The dummy for the treatment state controls for fixed differences between the two states, and the dummy for the post-treatment period controls for conditions that change for both states over time. The "X" term represents a vector of covariates, specifically a white/non-white dummy, a health coverage dummy, an ordinal measure of education, sex, and age. In the ACS microdata dataset, to achieve a sufficient sample of individuals receiving cash benefits, the state is used as the geographic area of analysis, and the state of interest is chosen based on which states were used to construct the synthetic control.

COLORADO – INCREASE IN MAXIMUM TANF BENEFITS

Synthetic Control

Figures 1 and 2 below explore the state-level administrative data using a synthetic control. Functionally, these graphs compare Colorado's data to a weighted average of states (the synthetic control) which was selected based on how closely it tracked Colorado on the dependent variable before the policy change in 2009. Along with the dependent variable, the software considers several independent variables: the general unemployment rate, median household income, and the percent of individuals with cash assistance. States that made changes to their welfare policies at similar times are excluded from the pool of states that can be used to construct the synthetic control.

Practically, the synthetic control can be thought of as "expected values" for Colorado based on data on the other states. Figure 1 shows us that Colorado's poverty rate did not rise in 2009 as much as would be expected based on the synthetic control, and in fact remained consistently below the synthetic control until 2016, despite tracking almost perfectly before the policy change. However, the magnitude is fairly small; the difference between treatment and control was .49 percentage points in 2009. This might suggest a modest, negative effect on the poverty rate from raising TANF benefits, in line with

Hypothesis 4. The effects on work seem dramatic, but also inconsistent. The graph for Colorado shows a large initial increase in the percentage of work-eligible TANF individuals participating in work, followed by a precipitous decrease until 2016. Meanwhile, the synthetic control shows a gradual increase over the same time period. In 2009, Colorado was 8 percentage points above its synthetic control for work participation, but in 2012, it was 11 percentage points below. This might suggest that raising benefits has a strong, negative impact on work rates among TANF recipients in the long-run, which is in line with Hypothesis 3, but the initial positive impact on work requirements makes this relationship somewhat ambiguous.

To test the statistical significance of a synthetic control analysis, "placebo" tests are run where every other state in the pool also has a synthetic control model run, with the treatment year set the same. Then, the magnitude of the "treatment effect" for each of the placebo states is tested against the magnitude effect for our state of interest (Colorado). In this case, seven other states recorded differences between their poverty level in 2009 and their synthetic control's poverty level in 2009 that were more negative than Colorado's. Thirty-one states recorded differences that were less negative than Colorado's, or positive. The remaining states were dropped because they either made some change to their welfare policy between 2008 and 2009, or the synthetic control model could not be successfully run. One popular method of quantifying the placebo test is to compare "RMSPE ratios", or "Root Mean Squared Prediction Error" ratios (Johnson, 2013). In this method, root-mean-squared "errors" between the observed values and the values for the synthetic control are calculated for each year, and the ratio between the Root Mean Squared Prediction Errors in the pre and post periods is calculated. Because the synthetic control model should create an accurate reflection of the observed values in the pre-period, before allowing for divergence due to treatment effect in the post-period, error values for the pre-period should be close to zero if the synthetic control is a good match, and error values for the post-period should be high if the policy change had an impact, meaning higher values of the RMSPE ratio is better. Among states with a negative effect in 2009 and 2010, eight states had a higher RMSPE ratio than Colorado. What all of this suggests is that it is somewhat unlikely (approximately a 20% chance) that an effect size similar to or greater than Colorado's may have been randomly observed in a state that made no adjustments to its welfare policy, making the result marginally significant. Although the work effects are extremely unusual for Colorado, and thus difficult to interpret, both the high value in 2009 and low value in 2012 would be considered statistically significant under this method. While several placebo states have larger treatment effects in the same direction in those two years, Colorado achieves an extremely large RMSPE ratio because the other states with large effect sizes had poor pre-treatment fit.

Another way of running a placebo test is to change the treatment year in the model, and see if a similar effect is identified regardless. Colorado appears to pass this placebo test. If the treatment year is changed to 2008 (one year before the actual treatment effect), the difference in treatment in 2008 is only .13 percentage points, just a quarter of the effect size observed when the treatment year is correctly set to 2009. This implies that the year of 2009 did represent an unusual shift in poverty for Colorado, which provides an argument in favor of the significance of the treatment effect on poverty.

Difference-in-Differences Model

The synthetic control model, when modeling for poverty rates, leaned heavily

on the state of Wisconsin; it was given 84.7% of the weight for the "synthetic Colorado". One way to explore the results further is to run a traditional difference-in-differences model between Colorado and Wisconsin using the full ACS data. The results show that the change in overall poverty rate is statistically significant, while effects on work are unclear, mainly because the sample size for individuals receiving public assistance is quite small. The coefficient on poverty rate for the estimator for the diff-in-diff treatment effect is -.0093, which can be interpreted as Colorado's poverty rate rising by about one percentage point less than Wisconsin's over the time period 2008 – 2010, holding constant state, year, race, health insurance, education level, sex, and age. This may seem like a small effect size, but consider that the mean increase in poverty for Wisconsin from 2008 was 2.7 percentage points (10.33 to 13.07). Colorado's difference-in-differences represents a 34% reduction in that increase.

Measuring work-related outcomes using this data has serious limitations. The sample of individuals who reported receiving public assistance income in the past year is very small, which raises standard errors and makes statistical significance difficult to prove, and the ACS does not differentiate TANF from other forms of cash public assistance such as Supplemental Security Income (SSI). Given that, the results do not show statistically significant outcomes on any of the work-related variables, including wage and welfare income combined, wage income, employment rates, and a categorical variable for the number of weeks worked in the past year.

KANSAS – INCREASE IN LENGTH OF WORST-CASE WORK-RELATED SANCTION

Synthetic Control

Kansas' results for the synthetic control show no apparent impact of the policy change on the overall poverty rate, and a negative impact on work rates among work-eligible TANF recipients. As can be seen in Figure 3, Kansas' poverty rate tracks well with its synthetic control both before and after the policy change, indicating that increasing the length of the worst-case work-related sanction had no real impact in comparison to expected values. The results for work participation can be seen in Figure 4. As is shown by the divergence between Kansas and its synthetic control before the policy change, the synthetic control method was less successful at estimating a comparable synthetic match. This means the results should be interpreted with caution. What is shown is that Kansas showed a negative change in work participation in the year of its policy change, while its synthetic control saw an uptick. However, the graph seems to show that Kansas is re-converging with its synthetic control, and is trending upwards, although these long-term effects cannot be necessarily be attributed to the policy change. The difference-in-differences is -12.9 percentage points for the period 2011 – 2013. The conclusion that can be drawn from this particular analysis is that increasing the length of sanctions may actually have some negative impacts on work participation. The reason for this is unclear; one possibility is discouragement.

The immediate, negative work effect appears to be significant. No placebo state had a larger negative treatment effect than Kansas in 2012, suggesting a statistically significant result. Only five of the placebo states (out of a total of 40) with negative treatment effects in 2012 and 2013 also had a higher RMSPE ratio than Kansas. One reason some states achieved a higher RMSPE ratio is that Kansas had an unusually high pre-treatment RMSPE, which gives slightly less confidence in the results because the initial fit with the synthetic control was somewhat poor. The synthetic control was unable to obtain a perfect match in

the pre-period of 2009-2011, as evidenced in Figure 4. The other placebo test, which uses an alternate treatment year to see if an effect still emerges, also suggests significance. Changing the treatment year in the equation to 2011 only shows a treatment effect of .06 percentage points in that year, which suggests that the specific treatment year of 2012 is significant.

Difference-in-Differences Model

The state weighted most heavily for Kansas' synthetic control, when measuring trends in poverty, is Nebraska, at 64.2% of the weight. The results of the difference-in-differences model, however, are not statistically significant. The effect on poverty rate is actually similar in magnitude to Colorado (-.007), but the variance is higher, which precludes statistical significance. This matches the result of the synthetic control method (no effect). If the window is widened to 2010-2014, the effect actually reverses direction (.002), highlighting the lack of a clear relationship. The effect sizes are also not significant with relation to the work outcomes, although the direction of the coefficients appears to be positive for total income and income from wages. There appears to be effectively no impact on employment or hours worked for this sample.

Conclusion and Proposals for Moving Forward

Of the initial hypotheses, support is found for #3 and #4: that higher benefits will depress employment, and that higher benefits will reduce poverty. The key finding of this analysis is that increasing welfare benefits appears to reduce poverty, an effect that was marginally significant in placebo tests for the synthetic control method, and highly significant in the traditional diff-in-diff regression between the states of Colorado and Wisconsin. The synthetic control method also suggests a long-term negative effect on work participation from increasing benefits, although that effect is muddied by the short-term increase in work participation. The traditional diff-in-diff regression shows positive impacts on total income, wage income, employment, and weeks worked, but none of those coefficients are statistically significant.

Both the synthetic control method and the traditional diff-in-diff suggested that increasing the duration of sanctions has neither a positive nor negative impact on the poverty rate. The two analytical methods are in conflict regarding work: the synthetic control method suggests that Kansas' hardening of sanctions decreased work rates among work-eligible TANF recipients, at statistically significant levels, while the traditional diff-in-diff using ACS data found positive but statistically insignificant differences with respect to total income, earned income, employment, and number of weeks worked among recipients of public assistance.

The policy implication is that increasing welfare benefits, while overall a net positive in the goal of reducing poverty, may depress work participation in the long-run. However, the results are ambiguous as to whether or not increasing the length of sanctions is the answer. Perhaps work supports, training, and subsidized employment would be more effective. These results are largely in line with the broader literature on this subject.

These results should be taken as motivation to pursue further research on this important topic, as the policy conclusions are not yet entirely clear. The suitability of other publicly available datasets, such as the Current Population Survey (CPS) and the Survey of Income and Program Participation (SIPP), should be explored, but rich, administrative microdata would allow for more extensive analyses than are allowed by publicly available datasets. Ideally, a panel dataset of TANF recipients would allow for individual fixed effects that control for all variables, observable and unobservable, that are constant over time for

the same person. A panel dataset also has the advantage of tracking a consistent group of individuals, even if they leave welfare. Other aspects of welfare rules which are not covered in this study, such as eligibility criteria, could also influence outcomes. Also, external validity could be enhanced by extending the analysis to more states. One of the limitations of this study is that it is unknown if the relationship between benefits (or sanctions) and the outcome variables is strictly linear. Benefits and sanctions may have diminishing returns at a certain point.

The gold standard, however, would be a randomized control trial that assign one group to higher benefits or harsher sanctions, while the other group maintains the status quo. The groups could be observed over the course of a year to determine whether the policy changes had any effect. When assignment is random, all factors other than treatment status will be distributed equally between participants in the different groups, and the treatment and control groups will be equal in expectation. This is the best way to ensure internal validity of the results. However, running such an experiment would be expensive, and possibly impractical, as randomly assigning some families to higher benefits could be seen as inequitable. Nonetheless, an RCT is by far the most valid method of establishing a causal effect.

Figure 1

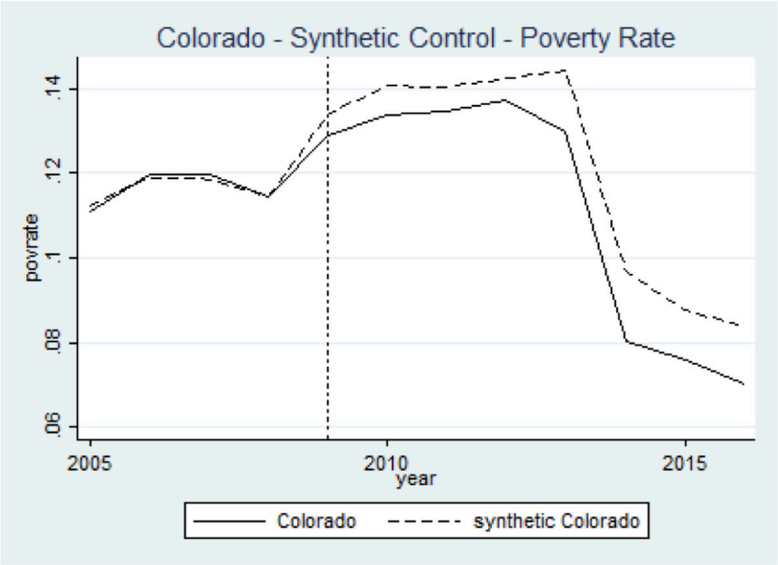

Figure 2

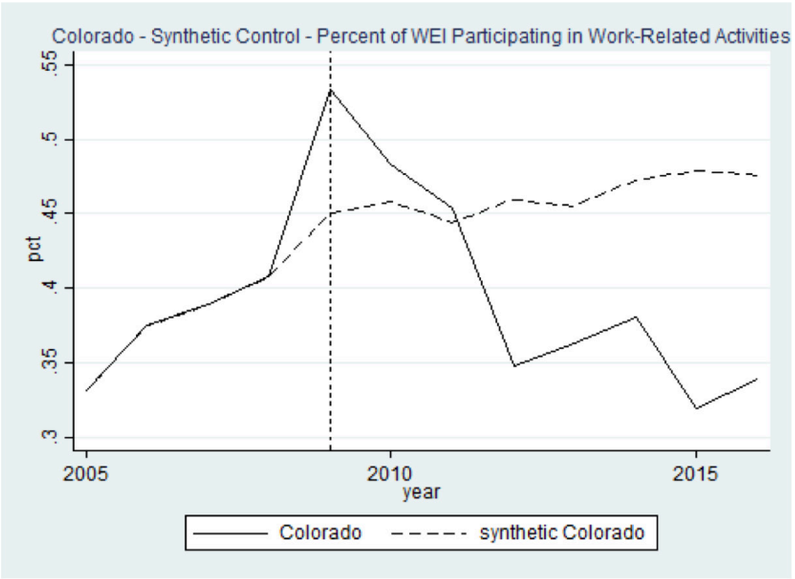

Figure 3

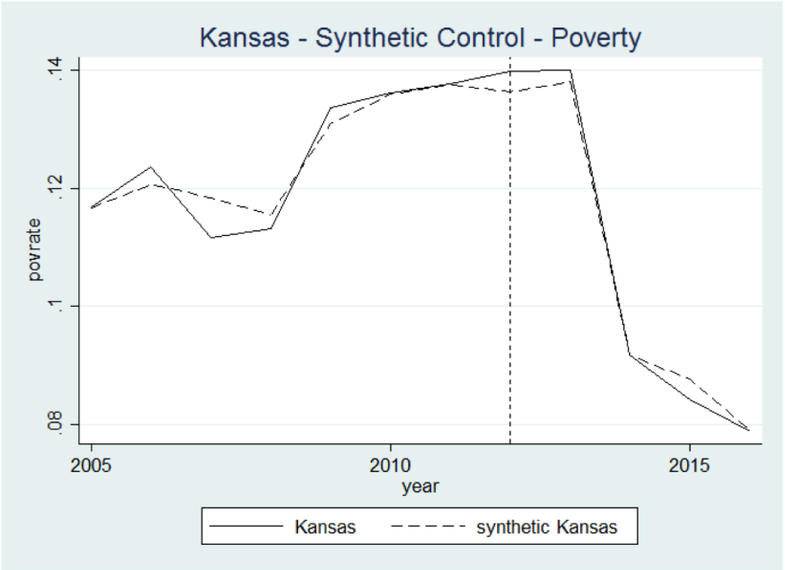

Figure 4

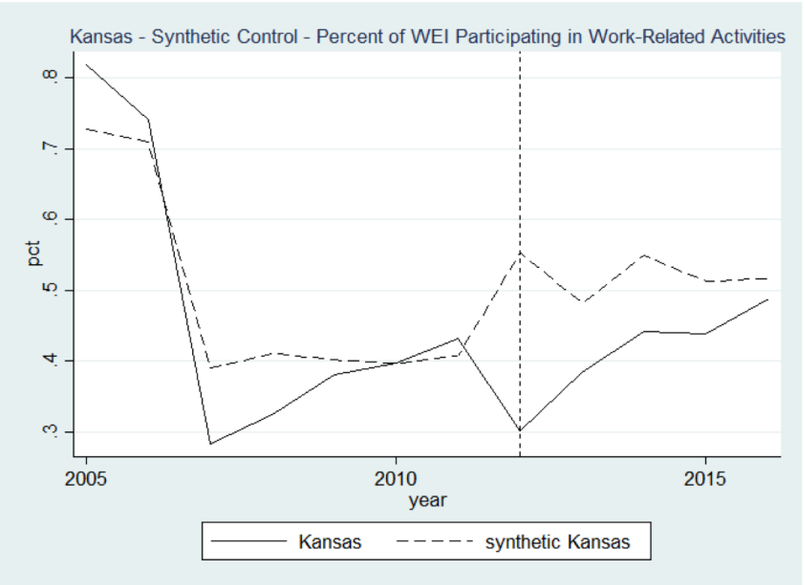

Figure 6

Diff-in-diff Colorado (Treatment) and Wisconsin (Control), 2008-2010

	povertyrate	inctot	incwage	employdum	wkswork2
colorado	0.000	-885.198	-517.791	-0.048	-0.339
	(0.003)	(1,163.016)	(1,153.787)	(0.058)	(0.263)
post2008	0.024	23.912	-18.487	-0.113	-0.299
	(0.002)***	(1,081.292)	(1,074.886)	(0.047)**	(0.215)
diff_in_diff_CO	-0.009	1,004.394	655.337	0.019	0.141
	(0.003)***	(1,439.326)	(1,425.511)	(0.070)	(0.311)
racwht	-0.113	2,087.524	2,246.474	0.133	0.297
	(0.003)***	(751.720)***	(734.027)***	(0.047)***	(0.200)
hcovany	-0.130	451.223	357.405	0.098	0.380
	(0.003)***	(1,348.775)	(1,309.740)	(0.048)**	(0.202)*
educ	-0.011	1,626.721	1,463.407	0.019	0.056
	(0.000)***	(212.683)***	(210.333)***	(0.008)**	(0.036)
sex	0.029	-4,900.270	-4,487.504	0.068	-0.012
	(0.002)***	(826.091)***	(822.381)***	(0.034)**	(0.141)
age	-0.001	-106.260	-114.428	0.002	0.012
	(0.000)***	(17.586)***	(17.105)***	(0.001)*	(0.005)**
_cons	0.399	6,749.114	4,723.130	0.343	2.699
	(0.005)***	(2,675.328)**	(2,605.053)*	(0.099)***	(0.429)***
R^2	0.06	0.10	0.09	0.05	0.03
N	323,378	2,665	2,665	1,225	1,229

* $p<0.1$; ** $p<0.05$; *** $p<0.01$

Figure 7

Diff-in-diff Kansas (Treatment) and Nebraska (Control), 2011-2013

	povertyrate	inctot	incwage	employdum	wkswork2
kansas	0.015	-306.140	-582.772	0.048	-0.304
	(0.005)***	(1,338.719)	(1,271.372)	(0.089)	(0.341)
post2011	0.004	-677.512	214.021	0.053	0.222
	(0.004)	(1,426.629)	(1,330.435)	(0.084)	(0.325)
diff_in_diff_KS	-0.007	2,926.516	1,818.023	-0.084	-0.105
	(0.006)	(1,841.152)	(1,744.905)	(0.110)	(0.432)
racwht	-0.089	38.953	811.793	0.070	0.254
	(0.006)***	(1,222.090)	(1,117.505)	(0.068)	(0.277)
hcovany	-0.164	1,848.640	1,425.305	0.210	0.047
	(0.005)***	(1,268.602)	(1,168.197)	(0.060)***	(0.257)
educ	-0.011	1,499.697	1,230.760	0.011	0.066
	(0.000)***	(251.470)***	(255.131)***	(0.012)	(0.056)
sex	0.031	-5,784.781	-5,401.436	-0.063	0.144
	(0.003)***	(1,227.259)***	(1,184.360)***	(0.050)	(0.212)
age	-0.001	-34.233	-52.688	0.004	0.017
	(0.000)***	(23.839)	(22.517)**	(0.002)*	(0.008)**
_cons	0.431	4,171.025	3,143.388	0.234	2.459
	(0.008)***	(3,100.624)	(2,968.356)	(0.149)	(0.632)***
R^2	0.07	0.09	0.07	0.05	0.03
N	143,923	1,443	1,443	696	712

* $p<0.1$; ** $p<0.05$; *** $p<0.01$

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