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ABSTRACT

The Personal Responsibility and Work Opportunity Reconciliation Act of 1996 established the Temporary Assistance for Needy Families (TANF) program within the United States. TANF mandated 60-month lifetime time limits for federal cash assistance dollars. Because states reserve the right to set their own stricter or more generous time limits, the 60-month lifetime limit did not bind in all cases. In recent years, however, several states imposed TANF time limits for the first time or made existing time limits more stringent. Using administrative and survey data, I find that stricter time limits decrease annual TANF participation by 22 percent and annual transfer income by 6 percent. Consistent with binding TANF work requirements, widespread unemployment, and increases in employment among those on the welfare caseload, stricter time limits do not tend to increase employment or earnings among single mothers in states without generous TANF programs at baseline. Evidence suggests that macroeconomic conditions and the labor market potential of TANF recipients play large roles in determining labor-supply effects of decreased TANF generosity.

JEL Classification Codes: H53, I38, J22

Key Words: Temporary Assistance for Needy Families; time limits; synthetic control method; difference-indifferences; participation

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1. Introduction

The Personal Responsibility and Work Opportunity Reconciliation Act of 1996 (PRWORA) established the Temporary Assistance for Needy Families (TANF) program within the United States. Perhaps the most controversial aspect of TANF was that it mandated 60-month lifetime time limits for federal cash assistance dollars. States, however, reserve the right to set stricter time limits or to continue to fund TANF caseloads beyond 60 months using their own funds. Earlier work on time limits, in which the authors of those earlier papers estimate the effects of welfare reform, suggests that states' introduction of time-limit policies decreases welfare use;[1] increases employment;[2] and decreases participation in the Supplemental Nutrition Assistance Program (SNAP), formerly the Food Stamp Program.[3]

In the wake of the Great Recession, several states have imposed TANF time limits for the first time or made existing time limits more stringent. I find that stricter time limits decrease annual TANF participation by 22 percent and annual transfer income by 6 percent among single prime-age female heads of household with children and without college degrees. Consistent with binding TANF work requirements, widespread unemployment, and increases in employment among those on the welfare caseload over time, stricter time limits do not tend to increase employment or earnings among single mothers in states without generous TANF programs at baseline. Evidence suggests that macroeconomic conditions and the labor market potential of TANF recipients play large roles in determining labor-supply effects of decreased TANF generosity.

I am the first to study time-limit policies implemented since 2003, which differ from the policies examined in earlier time-limit studies for several reasons. First, unlike time limits implemented circa 1996, more recent changes were not associated with other major welfare policy reforms, allowing me to isolate the effects of time-limit policies. Second, unlike the earlier time limits, the recent reforms counted families' existing months on welfare, so families beyond the time limit could lose eligibility and access immediately, which I refer to as a "mechanical" loss of eligibility.

[1]See Grogger (2002, 2003, 2004), Grogger and Michalopoulos (2003), Fang and Keane (2004), Swann (2005), Farrell et al. (2008), Ribar, Edelhoch, and Liu (2008), Fang and Silverman (2009), Mazzolari and Ragusa (2012), Chan (2013, 2017, 2018), and Low et al. (2018).

[2]See Grogger (2003), Fang and Keane (2004), Swann (2005), Farrell et al. (2008), Fang and Silverman (2009), Mazzolari and Ragusa (2012), Chan (2013, 2017), and Low et al. (2018).

[3]See Mazzolari and Ragusa (2012), Chan (2013), and Low et al. (2018).

Third, there are substantial macroeconomic differences and, therefore, differences in labor market opportunities between the 1990s and 2010s, which could lead to different effects of time-limit policies over time. Finally, the welfare caseload composition changed considerably between the 1990s and 2010s as PRWORA linked welfare to work and was wildly successful in decreasing welfare participation. Changes in the characteristics of those on the welfare caseload may also lead to differences in policy effects.

In the following section, I provide institutional details about the TANF policy environments. In Section 3, I present a conceptual framework for the effects of TANF time limits on access to financial resources. In Section 4, I describe the data. In Sections 5 and 6, I analyze TANF participation and other outcomes related to access to financial resources, respectively. In Section 7, I interpret results and discuss possible channels through which they may operate. In the eighth and final section, I conclude.

2. Background

TANF is a means-tested cash transfer program for families with children. The income, assets, and size of the assistance unit—children and any adults who care for them—determine households' eligibility for monthly cash assistance.[4] States set all policy parameters and administer TANF payments but receive about half their funding from the federal government if they meet spending requirements and have specified portions of their TANF caseloads engaged in work-related activities, such as employment and job training. States can use these federal TANF dollars to fund TANF cases with adults in the assistance unit who have received assistance for 60 months or fewer, as well as child-only cases in which children typically live with grandparents or other relatives. In other words, states may not allocate federal funding to children or adults in households that have received TANF for 60 months or more.[5] States, however, may continue to fund TANF cases beyond 60 months using their own funds or may implement shorter TANF time limits. While a few states

[4]An adult caretaker lives with the child and makes the majority of decisions regarding that child's well-being. States have discretion over whether adults who do not care for children are included in the assistance unit. For instance, some states include income from grandparents or stepparents living in the household when determining benefit amounts.

[5]States may use federal dollars to provide extended benefits for up to 20 percent of their average TANF caseload during times of hardship (Pub. L. 104-193. 110 Stat. 2105 2016). Children may continue to receive TANF benefits if they leave the household to live with grandparents or other friends or relatives.

allow all individuals to remain on TANF indefinitely, states more often grant certain groups of individuals exemptions from or extensions to their time-limit policies. For instance, many states extend time limits for victims of domestic violence and individuals who are ill or incapacitated.

Table 1 shows that four states, Arizona, Kansas, Maine, and Michigan—henceforth, the "analysis states"—changed their lifetime TANF time limits for all individuals in the assistance unit between 2010 and 2016. Arizona gradually shortened its time limit from 60 to 12 months between July 2010 and July 2016. Similarly, Kansas, which originally had a 60-month time limit, phased in a 24-month time limit between November 2011 and July 2016. Maine, which previously had no time limit, implemented a 60-month time limit in January 2012. And while Michigan formally established a 48-month time limit in 2007, Michigan's legislature did not implement this policy until 2011 and still allowed nearly all TANF cases to receive assistance for 60 months through time-limit extensions. Therefore, Michigan effectively implemented a 60-month time limit for the first time in 2011.[6] In all of these cases, the new time-limit policies were announced within a year of their implementation. Individuals who had already reached the states' new time limits were then notified. All individuals in assistance units that had reached their time limits, including children, were removed from the TANF caseload shortly after the time limits were implemented.

[6]Michigan's implementation of the 48-month state time limit led to the immediate closure of 0.2 percent of TANF cases (Carley 2011; Office of Family Assistance, Administration for Children and Families, United States Department of Health and Human Services 2020).

Table 1: State TANF Time Limit Policy Changes, 2003–2018

State	Time limit policy change	Month policy enacted	Affected individuals
Arizona	60 to 36 months	July 2010	All in assistance unit
Arizona	36 to 24 months	August 2011	All in assistance unit
Arizona	24 to 12 months	July 2016	All in assistance unit
California	60 to 48 months	July 2011	Adults in assistance unit
Kansas	60 to 48 months	November 2011	All in assistance unit
Kansas	48 to 36 months	July 2015	All in assistance unit
Kansas	36 to 24 months	July 2016	All in assistance unit
Maine	None to 60 months	January 2012	All in assistance unit
Michigan	None to 60 months	October 2011	All in assistance unit
Missouri	60 to 45 months	January 2016	All in assistance unit
Oregon	None to 60 months	October 2007	Adults in assistance unit
Rhode Island	None to 24 out of 60 months	July 2008	All in assistance unit

States that changed their TANF time-limit policies between 2003 and 2018. Information was retrieved from Urban Institute (2020).

Additionally, Table 1 shows that California, Missouri, Oregon, and Rhode Island changed their TANF time-limit policies between 2007 and 2016.[7] California and Oregon changed their time-limit policies for adults, but not children, in the assistance unit in 2011 and 2007, respectively. When TANF cases in these states reach their time limits, adults are removed from the caseload, while children remain eligible for benefits. Missouri also changed its time limit from 60 to 45 months in 2016, and Rhode Island implemented an intermittent, not lifetime, time limit in 2008. In this paper, I focus on the states that changed their lifetime time limits for entire families in the wake of the Great Recession; my period of study runs from 2007 through 2016. I do not estimate effects of time-limit policies enacted in 2007 and 2008 in Oregon and Rhode Island, but I do show results for California's modified time limit in the online appendix. To compare effects across macroeconomic environments, in the online appendix I also include results for Missouri, for which I extend the study period through 2018. I remove Oregon, Rhode Island, California, and Missouri from the main analyses.[8]

Anecdotal evidence suggests that the states in Table 1, and the analysis states in particular, implemented stricter TANF time-limit policies in response to economic difficulties which became

[7]While Washington formally introduced a stricter TANF time-limit policy in 2011, it continued to allow individuals who complied with TANF policies to remain on the caseload indefinitely.

[8]I also remove Illinois from the analyses, as it experienced a budget shortfall in 2012 that caused some TANF benefit payments to be delayed until 2013.

particularly pressing in the absence of federal supports after the Great Recession. Specifically, during Fiscal Years 2009 and 2010, states could receive additional federal TANF funds through the American Recovery and Reinvestment Act of 2009 (ARRA), which allocated $5 billion toward emergency TANF spending (Pub. L. 111-5 2009). But when ARRA appropriations ended in 2011, some state governments found themselves struggling to fund TANF caseloads. In particular, analysis states were experiencing budget shortfalls as they changed their time-limit policies (Oliff, Mai, and Palacios 2012). In Arizona's *TANF Caseload Reduction Report* for Fiscal Year 2010, Brewer and Young (2013) explain that the Arizona Department of Economic Security's budget was cut by more than 31 percent between the beginning of Fiscal Year 2009 and the end of Fiscal Year 2010. They claim that additional cuts would have been necessary in the absence of the ARRA appropriations. Likewise, Michigan forecast nearly $75 million in cost savings due to time-limit case closures during Fiscal Year 2012 (Carley 2011). In light of this, and given the high unemployment rates in the wake of the Great Recession, state financial issues, rather than a lack of need for safety-net benefits, seem to have driven states to change their TANF time limits.

Time limits are not the only margin along which states can influence TANF program design, as each state sets its own income eligibility requirements, TANF benefits, and work requirements for recipients. While each of these policies varies to some degree across states, many states implement similar TANF program rules. For instance, most states, including all of the analysis states, calculate TANF benefit amounts using the following formula:

$$TANFBenefit = Max\{MaxBenefit - t(Y - D), 0\}, \tag{1}$$

where $MaxBenefit$ is the maximum TANF benefit, a function of family characteristics; Y is non-TANF income; $D \in [0, \infty)$ is the earned income disregard; and $t \in (0, 1]$ is the benefit reduction rate. Hence, after some amount of earned income is disregarded, additional income decreases TANF benefits. Additionally, many states require their TANF recipients without very young children to engage in work-related activities, such as employment and job training, for at least 30 hours per week.

Table 2 displays how some state TANF program rules varied across the analysis states and the rest of the United States between 1999 and 2009. For three-person families, both maximum TANF benefits and maximum income thresholds for eligibility have increased little, if at all, in nominal terms in each of the analysis states and in the remaining U.S. states on average, suggesting that TANF has become a less generous program over time. Table 2 also shows that TANF generosity varies considerably across the analysis states. For instance, as of 2009, the monthly income threshold for initial TANF eligibility of three-person families was more than $1,000 in Maine but less than $600 in both Arizona and Kansas. TANF benefit formula parameters differ across analysis states as well. And while work requirements are fairly similar across analysis states, exemptions from work requirements for parents of young children differ considerably. Maine, Kansas, and Michigan exempt parents of children 12, 6, and 3 months or younger, respectively, while Arizona does not exempt any parents from work requirements on the basis of the age of the child.

Table 2: State TANF Policies over Time

		Arizona	Kansas	Maine	Michigan	Control mean/mode
Time limit						
	1999	None	60	60	None	60
	2004	60	60	None	None	60
	2009	60	60	None	None	60
Max income ($)						
	1999	586	519	1,023	774	692
	2004	586	519	1,023	774	731
	2009	585	519	1,023	815	777
Max benefit ($)						
	1999	347	429	461	459	408
	2004	347	429	485	459	414
	2009	278	429	485	492	400
Earned income disregard ($)						
	1999	90	90	108	200	
	2004	90	90	108	200	
	2009	90	90	108	200	
Benefit reduction rate (%)						
	1999	70	60	50	80	
	2004	70	60	50	80	
	2009	70	60	50	80	
Work requirement						
	1999	Case-specific	25	25	25	25
	2004	Case-specific	30	30	40	30
	2009	Case-specific	30	30	30	30
Child younger than (months)						
	1999	N/A	12	12	3	12
	2004	N/A	12	12	3	12
	2009	N/A	6	12	3	12

Policies for nonelderly, nonexempt adults in standard state TANF programs as of July 1999, July 2004, and July 2009. "Time limit" indicates the state's lifetime time limit. "Max income" indicates the maximum income level for initial eligibility of three-person families. "Max benefit" indicates the maximum benefit amount for three-person families. "Earned income disregard" indicates the state's earned income disregard for TANF benefits. "Benefit reduction rate" indicates the state's benefit reduction rate for TANF benefits. "Work requirement" indicates parental weekly work requirements. "Child younger than (months)" indicates the age of the child for which parents are exempt from work requirements. The column "Control mean/mode" displays means across all states except the analysis states for maximum income and benefits, as well as modes for time limits, work requirements, and exemptions from work requirements for parents of young children. Information was retrieved from Urban Institute (2020).

In addition to TANF policies, welfare caseload composition has changed over time as PRWORA led to large decreases in welfare participation and tied welfare receipt to work. Table 3 uses data from the 1990 census and the 2009 American Community Survey (ACS) to show stark differences between adult welfare recipients with children in 1990 and 2009 (Ruggles et al. 2020).[9] On average, welfare recipients in 2009 are younger and have more children than welfare recipients in 1990. In addition, welfare recipients in 2009 are 12 percentage points more likely to be employed and earn about $3,600 (2010 dollars) more annually than welfare recipients did in 1990, in spite of higher unemployment rates during the Great Recession.

[9] I limit the sample to welfare recipients with children to eliminate child-only cases. I also restrict the sample to those with less than $80,000 in earnings to remove outliers from the data.

Table 3: Summary Statistics for Welfare Recipients in 1990 and 2009

	1990	2009	Difference
Female	0.81	0.80	-0.01
	(0.0011)	(0.0041)	{0.0075}
Married	0.30	0.32	0.02
	(0.0013)	(0.0049)	{0.0006}
Age	40.61	37.85	-2.76
	(0.0483)	(0.1340)	{0.0000}
White	0.49	0.48	-0.01
	(0.0014)	(0.0054)	{0.0027}
Black	0.29	0.23	-0.06
	(0.0013)	(0.0048)	{0.0000}
Hispanic	0.07	0.12	0.05
	(0.0007)	(0.0036)	{0.0000}
Kids	2.10	2.17	0.07
	(0.0036)	(0.0137)	{0.0000}
Kids <5	0.56	0.63	0.07
	(0.0023)	(0.0092)	{0.0000}
<High school	0.52	0.31	-0.21
	(0.0014)	(0.0051)	{0.0000}
High school	0.28	0.31	0.03
	(0.0013)	(0.0051)	{0.0000}
>High school	0.20	0.38	0.18
	(0.0012)	(0.0053)	{0.0000}
Employed	0.21	0.33	0.12
	(0.0012)	(0.0051)	{0.0000}
Earnings	3,690	7,316	3,626
	(27)	(128)	{0.0000}
Observations	154,844	12,413	
Representative of	3,143,241	1,340,208	

Summary statistics for parents who received TANF in 1990 and 2009. "Employed" is an indicator for work within the past week. "Earnings" indicates annual earnings. Data was retrieved from the 1990 census and the 2009 ACS using household weights. Standard deviations are listed in parentheses. p-values are listed in curly braces.

Under both the 1990s and 2010s environments, the TANF program interacted with other elements of the safety net. For example, households that receive TANF are categorically eligible for SNAP, which provides food benefits to needy households. Because of this, TANF recipients need not apply for SNAP or meet its income and asset requirements. Although virtually all households that leave TANF remain eligible for SNAP, they must reapply for benefits. While some states, including Arizona and Maine, allow households to maintain categorical SNAP eligibility for up to five months after leaving TANF through transitional benefits, former TANF recipients in other states lose SNAP eligibility concurrently with TANF eligibility if they fail to reapply (Food and Nutrition Service, United States Department of Agriculture 2019b). Transaction costs involved in SNAP certification are nontrivial, and evidence suggests that they likely prevent take-up among eligibles (Currie and Grogger 2001; Ziliak, Gundersen, and Figlio 2003; Ribar, Edelhoch, and Liu 2008; Homonoff and Somerville 2020), so stricter TANF time-limit policies likely disconnect households from SNAP, decreasing their access to financial resources.[10]

In existing work, authors also find that decreased welfare generosity is associated with increased participation in the Supplemental Security Income (SSI) program (Kubik 1999; Bowen and Glied 2000; Schmidt and Sevak 2004). SSI is a means-tested federal transfer program that provides cash and Medicaid benefits to low-income individuals who are 65 years of age or older, blind, or disabled. Unlike TANF, SSI is administered at the individual level, and there are no time limits or work requirements. Similarly to TANF, however, SSI benefits decrease with household income.

In terms of incentives, both states and households benefit from moving adults and children with disabilities from TANF to SSI. When this occurs, the SSI recipient is no longer part of the TANF assistance unit. This leads to a decrease in TANF benefits, but SSI benefits are more generous, and the SSI recipient's income does not count in the TANF benefit calculation.[11] The state also benefits from the individual's shift to SSI as the federal government funds the SSI program.[12]

Low-income families who become disconnected from TANF face an increased incentive to enroll their members in SSI, as they no longer face a trade-off between decreased TANF and increased SSI benefits. Nonetheless, applying for SSI is time consuming, and Deshpande and Li (2019) document a spike between 2011 and 2014 in closures of Social Security Administration (SSA) field offices, at which individuals can receive assistance in completing SSI applications. In particular, SSA field offices closed in Kansas, Maine, and Michigan during that time. Increased costs of SSI take-up in these states may prevent substitution toward SSI in the absence of TANF.

[10]Since SNAP benefits are a function of family size and income less several deductions, TANF receipt may decrease SNAP benefit amounts in some cases. Nonetheless, TANF benefit receipt does not affect SNAP benefit amounts among very-low-income families that receive the maximum SNAP benefit.

[11]The maximum monthly federal SSI benefit for an individual was $674 as of January 2009 (Social Security Administration 2009). This is larger than the maximum TANF benefit for a three-person family as of July 2009 in each of the analysis states (Urban Institute 2020).

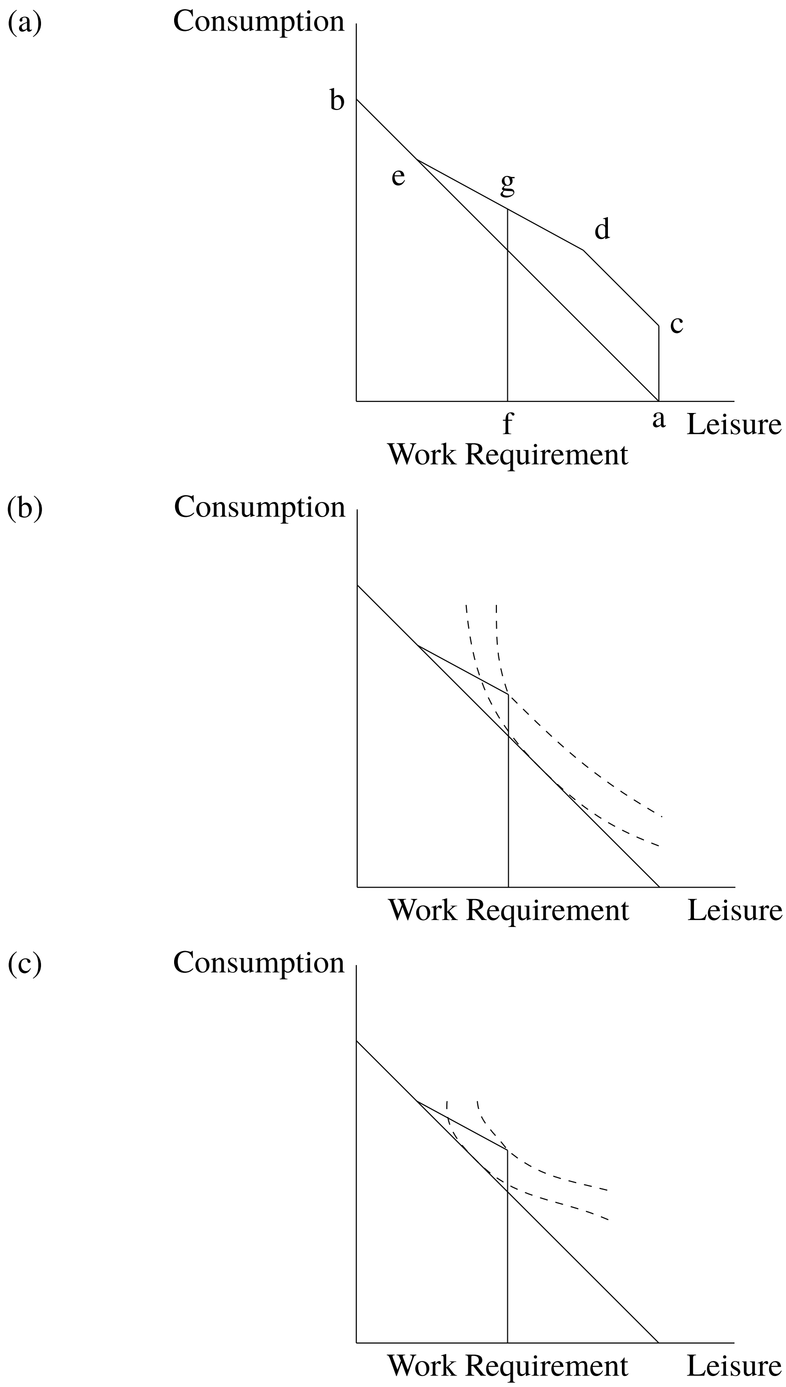
[12]Most states provide small supplements to SSI benefits using their own funds.

Finally, stricter time-limit policy effects on earnings may lead to changes in tax benefits among TANF-vulnerable individuals. In particular, the Earned Income Tax Credit (EITC), a refundable tax credit targeted at low- and moderate-income households with children, serves as an earnings subsidy. For virtually all workers who meet TANF income-eligibility requirements, the EITC generates a work incentive by decreasing the marginal tax rate on earned income.

3. Conceptual Framework for Time Limits and Access to Financial Resources

In this section, I discuss how TANF labor-supply incentives may affect families' access to financial resources, including implications of work requirements and time limits. First, suppose that individuals only receive labor income. In each period, they face a trade-off between consumption and leisure, as illustrated by the budget constraint, line segment $\overline{ab}$ in Panel (a) of Figure 1. Now, suppose that TANF is available but that work is *not* required to receive benefits. Then, the budget constraint becomes $\overline{acdeb}$. Individuals who do not work are guaranteed a consumption floor and locate at point c. The vertical distance between points c and d represents the earned income disregard, and the slope of line segment $\overline{de}$ is the benefit reduction rate. In this case, individuals who become disconnected from TANF face a negative income and a (weakly) negative substitution effect that imply increases in labor supply.

Figure 1: Static Model of Labor Supply



Static model of labor supply with and without TANF. Solid lines represent budget constraints, and dashed lines represent indifference curves.

Next, suppose that individuals face a work requirement and must locate along line segment $\overline{ge}$

to receive TANF benefits.[13] The budget constraint is now $\overline{afgeb}$. If the work requirement binds, then it is unclear whether individuals will increase or decrease their labor supply in the absence of TANF. For example, an individual with preferences represented by the dashed indifference curves in Panel (b) of Figure 1 decreases labor supply when TANF becomes unavailable, while another individual with preferences represented by the indifference curves in Panel (c) of Figure 1 increases labor supply under the same constraints.

In addition, in the presence of fixed costs of supplying labor, extensive-margin labor supply may change in the absence of TANF. Specifically, if the fixed cost of supplying labor is strictly positive but less than line segment $\overline{fg}$, then individuals may leave the labor force when TANF becomes unavailable. Furthermore, individuals who qualify for SSI may begin to take up SSI benefits in the absence of TANF. As SSI benefits are more generous than TANF benefits and eligibility is not tied to work requirements, substitution toward SSI likely leads to decreases in labor supply. Taken together, decreased TANF benefits, labor-supply responses, and changes in benefits from other social-safety-net programs likely interact in a complicated way to affect individuals' access to financial resources.

Finally, TANF-vulnerable families who have not yet reached their time limits face an intertemporal trade-off between TANF participation in the current period and consumption and insurance against negative income shocks in future periods. In existing work, authors find that welfare recipients are forward-looking and bank TANF benefits for the future.[14] Nonetheless, individuals in Arizona and Kansas, for example, who face relatively short time limits, may be limited in their capacity to save TANF for future periods. Hence, while short time limits may decrease TANF use by deeming families ineligible for benefits, behavioral TANF participation effects likely are more muted in these states, where recipients retain limited ability to smooth consumption over time.

[13]For work activities other than employment, individuals would have to supply the same amount of labor to receive TANF benefits but would only consume those TANF benefits in the absence of additional earnings.

[14]See Grogger (2002, 2003, 2004), Grogger and Michalopoulos (2003), Swann (2005), Ribar, Edelhoch, and Liu (2008), Mazzolari and Ragusa (2012), Chan (2013, 2017, 2018), and Low et al. (2018).

4. Data

I use two primary sources of data: 1) monthly state-level administrative data from the U.S. Department of Health and Human Services, Office of Family Assistance, from January 2007 through December 2016, (Office of Family Assistance, Administration for Children and Families, United States Department of Health and Human Services 2020) and 2) annual household-level survey data from the ACS from 2007 through 2016 (Ruggles et al. 2020). The administrative data document each state's number of adult TANF recipients by month and are not subject to reporting issues that plague household survey data. Meyer, Mok, and Sullivan (2015) document severe underreporting of safety-net benefits in household surveys, and Meyer and Wu (2018) show that such underreporting can lead to substantial underestimates of the effects of TANF on poverty. The administrative data exhibit some problems, however. During the sample period, a number of states, including California and Maine, began to provide token payments to working individuals in an effort to satisfy the federal work requirement. Specifically, states can provide token payments to individuals who leave the TANF caseload for employment, in order to boost state work-participation rates and ensure federal funding. But when states introduce or eliminate these token payments, the sizes of their TANF caseloads can change substantially, making the administrative data reported by these states a poor measure of trends in traditional TANF participation. For example, after Maine instated a $15 food-benefit-payment program in 2012, the state's reported number of adult TANF recipients nearly tripled (Office of Family Assistance, Administration for Children and Families, United States Department of Health and Human Services 2020). This created a spike in the data that does not reflect a change in traditional TANF use.[15]

The ACS data come from a state-representative survey of about three million households and document individuals' demographics and economic outcomes, including TANF benefits within the past year.[16] Fortunately, changes in TANF participation due to token payments do not appear

[15]In conversations with me, employees at Delaware's Health and Social Services, Kentucky's Cabinet for Health and Family Services, and Vermont's Agency of Human Services confirmed programming glitches or reporting errors in their states' TANF data as reported on the website of the U.S. Department of Health and Human Services, Office of Family Assistance. I drop Delaware, Kentucky, Ohio, and Vermont in analyses using administrative data because of changes in token payment policies and TANF reporting errors. Results are robust to including these states in the analyses and can be found in the online appendix.

[16]ACS respondents are asked to report "any public assistance or welfare payments from the state or local welfare office" within the past year (Ruggles et al. 2020). This measure includes both TANF and General Assistance (GA)

to materialize in the ACS data, probably because many states provided these payments in the form of food benefits, which survey respondents are unlikely to report as welfare income. After establishing that stricter time-limit policies affect TANF participation, I use these data to study access to financial resources as proxied by labor supply, income, and participation in other safety-net programs. In the ACS, I observe households' SNAP and SSI participation during the past year and individuals' work during the past week and annual income from various sources.[17] I do not observe SNAP benefits or other federal and state taxes and subsidies, such as the EITC, directly but impute these measures using households' demographic information, SNAP parameters (Food and Nutrition Service, United States Department of Agriculture 2019a), and the National Bureau of Economic Research's (NBER) TAXSIM program (Feenberg 2017a). More specifically, among households that report SNAP participation, I use their family sizes, income, and housing costs, among other demographics, to impute annual benefit amounts. Similarly, TAXSIM simulates individuals' annual state and federal taxes, including EITC benefits.[18] I then use imputed SNAP benefits and taxes, combined with reported total income, to calculate what I refer to as "total resources": total individual posttax income plus SNAP benefits.[19]

For analyses of outcomes other than TANF participation, I isolate the population most affected by TANF policies by limiting the sample to female heads of household aged 18 to 54 with children, no spouse present, and less than a bachelor's degree.[20] Under these restrictions, I capture most of the TANF-vulnerable population, as 86 percent of TANF recipients are female, 86 percent are single, and less than five percent have more than 12 years of education (Office of Family Assistance, Administration for Children and Families, United States Department of Health and Human Services 2020). There are about 335,000 women in the restricted sample. Table 4 displays summary statistics from 2007 through 2009, a period before any state changed its time limit, and

benefits, but given the extremely small size of the GA program (Schott and Hill 2015), it should be a nearly perfect measure of reported TANF benefits. Because I do not observe the respondent's interview month, I code outcomes during the past year as having occurred during the survey year.

[17]While work during the past week may be an imperfect measure of employment, data from the Current Population Survey (CPS) suggest that nearly all full-time employees are at work during a given week (Bureau of Labor Statistics, United States Department of Labor 2018).

[18]I do not observe EITC participation but assume that eligible taxpayers take up the credit, as over 78 percent of EITC-eligible single filers had taken up the EITC as of 2009 (Jones 2014).

[19]Details of both the SNAP and tax imputation procedures can be found in the online appendix.

[20]I restrict the sample to women with less than $80,000 in total resources to remove outliers from the data. This reduces the sample size by 1 percent. Results in which I include women with $80,000 or more in total resources in the analyses are similar.

notes statistical differences between outcomes in each analysis state and the control region, which consists of all remaining U.S. states except California, Illinois, Missouri, Oregon, and Rhode Island, for reasons explained in Section 2. Table 4 confirms that there are high rates of program participation within the sample: 8 percent of women in the control region report TANF use within a given year, with 40 percent reporting SNAP participation. Program participation is especially high in Maine, where 24 percent of women receive TANF; this is more than 15 times higher than the adult TANF participation rate within the U.S. more broadly. In conjunction with high rates of program participation, women have low income levels. In the control region, average total resources are $24,899 (2010 dollars), and this measure ranges from around $23,500 to $26,000 across Arizona, Kansas, Maine, and Michigan. These low income levels are in spite of relatively high labor-force participation rates. Some 71 percent of women in the control region and 70 to 76 percent of women across the analysis states reported working during the past week.

Table 4: Summary Statistics for ACS Target Sample

	Arizona	Kansas	Maine	Michigan	Control
Age	35.55**	33.61***	35.41	35.51**	35.15
	(0.1816)	(0.3119)	(0.4577)	(0.1555)	(0.0322)
White	0.42***	0.67***	0.93***	0.60***	0.48
	(0.0112)	(0.0188)	(0.0148)	(0.0093)	(0.0019)
Black	0.06***	0.14***	0.02***	0.31	0.31
	(0.0054)	(0.0146)	(0.0090)	(0.0089)	(0.0018)
Hispanic	0.29***	0.07***	0.00***	0.03***	0.10
	(0.0106)	(0.0719)	(0.0014)	(0.0036)	(0.0012)
Kids	2.14***	2.03	1.79***	2.00	1.97
	(0.0254)	(0.0419)	(0.0490)	(0.0204)	(0.0041)
Kids <5	0.47	0.56***	0.37**	0.42**	0.45
	(0.0162)	(0.0317)	(0.0323)	(0.0125)	(0.0028)
<High school	0.17***	0.16	0.08***	0.14***	0.17
	(0.0015)	(0.0150)	(0.0173)	(0.0068)	(0.0015)
High school	0.29***	0.35	0.42***	0.33**	0.35
	(0.0105)	(0.0189)	(0.0284)	(0.0086)	(0.0019)
Some college	0.49	0.49	0.50	0.53***	0.48
	(0.0113)	(0.0195)	(0.0287)	(0.0093)	(0.0019)
TANF	0.07*	0.12**	0.24***	0.14***	0.08
	(0.0059)	(0.0135)	(0.0258)	(0.0063)	(0.0011)
SNAP	0.37**	0.35*	0.53***	0.50***	0.40
	(0.3730)	(0.0192)	(0.0285)	(0.0093)	(0.3979)
SSI	0.02***	0.02	0.04	0.03	0.03
	(0.0029)	(0.0059)	(0.0093)	(0.0031)	(0.0007)
Employed	0.72	0.76***	0.71	0.70*	0.71
	(0.0102)	(0.0167)	(0.0264)	(0.0085)	(0.0018)
TANF income	256	288	715***	459***	260
	(36)	(43)	(96)	(28)	(5)
SNAP benefits	1,496	1,432	1,559	2,032***	1,581
	(59)	(108)	(123)	(53)	(10)
SSI income	114***	173	315	203	207
	(21)	(44)	(73)	(21)	(5)
Earnings	20,069***	19,080	16,159***	17,812**	18,514
	(381)	(591)	(877)	(312)	(64)
EITC	1,700***	2,280***	1,881	1,871	1,855
	(40)	(78)	(105)	(49)	(7)
Total resources	25,876***	25,931**	23,502*	25,379*	24,899
	(334)	(492)	(725)	(255)	(55)
Observations	2,762	1,068	523	4,524	97,090
Representative of	320,802	142,747	69,899	559,813	11,973,679

Summary statistics for female heads of household aged 18 to 54 with children, no spouse present, and less than a bachelor's degree. "TANF," "SNAP," and "SSI" are indicators for household TANF, SNAP, and SSI use within the past year, respectively. "Employed" is an indicator for work during the past week. Income measures are annual, and "Total resources" denotes posttax cash and near-cash income. Data was retrieved from ACS years 2007 through 2009 using household weights. Standard deviations are listed in parentheses. Asterisks denote significance at the 1% (***), 5% (**), and 10% (*) levels. Statistical significance is relative to the control region.

Sample demographics vary across analysis states. For instance, while Kansas, Maine, and Michigan exhibit large proportions of white individuals, Arizona has a large Hispanic population. Additionally, women in Arizona, Kansas, Michigan, and the control region have at least 2.0 children on average, while women in Maine have 1.8 children on average. Women in Maine also tend to have fewer children younger than five years old than do women in the other analysis states and the control region.

Given the sample demographics, income, program participation, and employment should be good indicators of access to financial resources among these women. The women likely do not own large sums of assets, and because they have low income levels on average, even small changes in income may affect their standards of living. Additionally, the high rates of program participation within the sample suggest that safety-net benefits play an important role in determining such living conditions.

5. TANF Participation

5.1. Empirical Strategy

Using both the administrative and ACS data, I first study each analysis state separately so that I can observe heterogeneous effects across state policy environments. I then estimate specifications in which I pool analysis states into a single treated unit to obtain an average estimated treatment effect.

I begin by estimating synthetic control models of TANF participation using the administrative data (Abadie and Gardeazabal 2003; Abadie, Diamond, and Hainmueller 2010). The synthetic control method allows state-specific characteristics to vary over time. This is particularly important when studying the effects of welfare time limits, for the descriptive evidence documented in Section 2 suggests that analysis states changed their time limits in response to the Great Recession's effects on their economies. If this is true, then welfare participation in analysis states likely would have increased disproportionately in the absence of their policy changes, as more individuals would have qualified for TANF benefits. In this case, failing to control for time-varying state-specific characteristics leads one to underestimate the effects of stricter time-limit policies on welfare participation. By allowing state-specific characteristics to vary over time, the synthetic control method obtains the causal effects of stricter time-limit policies on TANF participation as long as the synthetic control unit, a weighted average of the control states, provides a good approximation of the treated state's TANF participation trajectory in the absence of treatment.

I estimate the following synthetic control model for each analysis state separately:

$$Y_{st} = \beta TimeLimit_{st} + \mu_s \delta_t + \theta_{st}\phi + \epsilon_{st}, \tag{2}$$

where Y_{st} is the number of adult TANF recipients per 100 adults (Population Division, United States Census Bureau 2020) in states s during month t. $TimeLimit_{st}$ is an indicator for the state policy change. Specifically, $TimeLimit_{st}$ changes from 0 to 1 in the treatment region during the month in which the state first changed its time-limit policy and stays "turned on" throughout the remainder of the sample period. δ_t is a vector of unobserved common factors, and μ_s is a vector of unknown factor loadings. θ_{st} is a vector of state characteristics, including the state's unemployment rate (Bureau of Labor Statistics, United States Department of Labor 2020), inflation-adjusted minimum wage (Office of Communications, Wage and Hour Division, United States Department of Labor 2020), TANF program parameters (Urban Institute 2020), and an indicator for transitional SNAP benefits (Food and Nutrition Service, United States Department of Agriculture 2019b).[21]. I also control for the state's annual revenues less expenditures (United States Census Burea 2020) and number of Social Security Administration field offices (Social Security Administration 2017), both relative to the size of its adult population. ϵ_{st} is the error term. β is the coefficient of interest and captures the difference between the treatment state and the synthetic control unit during each posttreatment period, the causal effect of time limits on TANF use.[22]

I then extend the original synthetic control approach to a setting with multiple treated units, pooling the four analysis states into a single affected unit (Dube and Zipperer 2015; Kreif et al. 2016; Dickert-Conlin, Elder, and Teltser 2019). To do so, I rescale time into months relative to the policy change and randomly assign a synthetic policy change month to each control state. To create a

[21]The state TANF program parameters include the maximum TANF benefit and maximum income for TANF eligibility, as well as indicators for whether the state requires a job search at the time of TANF application and whether failure to meet work requirements can result in loss of benefits on the first offense.

[22]When estimating Equation (2), I average lagged TANF participation values over periods of three pretreatment months to avoid model overfit. Hence, each post-treatment time period consists of three consecutive months.

balanced panel, I limit the sample to observations that occurred up to 45 months before and up to 61 months after the (synthetic) policy change. I then estimate Equation (2).

To compare results across states, I calculate the mean of the elements of $\hat{\beta}$, measuring the average estimated treatment effect during the posttreatment period. Denote this measure as $\tilde{\beta}$. While the synthetic control method does not produce standard errors on $\tilde{\beta}$, I measure the probability that sampling variation drives treatment effects using placebo tests (Abadie and Gardeazabal 2003; Abadie, Diamond, and Hainmueller 2010). When the magnitude of the actual average treatment effect is larger than that of nearly any placebo treatment during the posttreatment period, the probability that sampling variation drives treatment effects likely is small. To take into account placebo estimates with poor pretreatment fit, I display figures of the distribution of the ratio of post- to pretreatment root-mean-squared prediction error (RMSPE) (Abadie, Diamond, and Hainmueller 2010). If the actual analysis state exhibits good pretreatment fit and a large estimated effect size, then its RMSPE ratio will lie in the right tail of the distribution, indicating that obtaining an RMSPE ratio as large would be a low probability event had the treatment been randomly assigned within the data.

The monthly administrative data contain many lags of the TANF participation measure, which are used in the matching process and generally lead to a small RMSPE during the pretreatment period. The annual ACS data, however, do not contain many lags of the dependent variable and therefore are not as well suited to estimate Equation (2).[23] Because of this, I also estimate difference-in-differences models of TANF participation. The difference-in-differences models rely on the assumption of common trends between the treatment and control regions that would not have changed during the posttreatment period, had the analysis state not changed its time-limit policy.

I estimate the following difference-in-differences model using the administrative data:

$$Y_{st} = \beta TimeLimit_{st} + \mu_s + \delta_t + \theta_{st}\phi + \epsilon_{st}, \tag{3}$$

where Y_{st} is the number of adult TANF recipients per 100 adults in state s during month t, as in Equation (2). $TimeLimit_{st}$ is again an indicator for the state policy change that is a "1" in the treatment region during the posttreatment period. μ_s and δ_t are state and month fixed effects,

[23]Synthetic control figures using the ACS data can be found in the online appendix.

respectively. θ_{st} is a vector of state characteristics. ϵ_{st} is the error term. I cluster standard errors at the state level.

I estimate a similar difference-in-differences model using the ACS data:

$$Y_{ist} = \beta TimeLimit_{st} + \mu_s + \delta_t + \theta_{st}\phi + X_{ist}\Gamma + \epsilon_{ist}, \tag{4}$$

where Y_{ist} is a scaled indicator of TANF participation that equals 100 if individual i in state s participated in TANF during year t. (This scaling makes Y_{ist} comparable to Y_{st} from Equation [3].) Similar to Equation (3), $TimeLimit_{st}$ is an indicator for the state policy change, μ_s represents state fixed effects, δ_t represents year fixed effects, and θ_{st} is a vector of state characteristics. X_{ist} is a vector of individual characteristics.[24] ϵ_{ist} is the error term. I again cluster standard errors at the state level.[25]

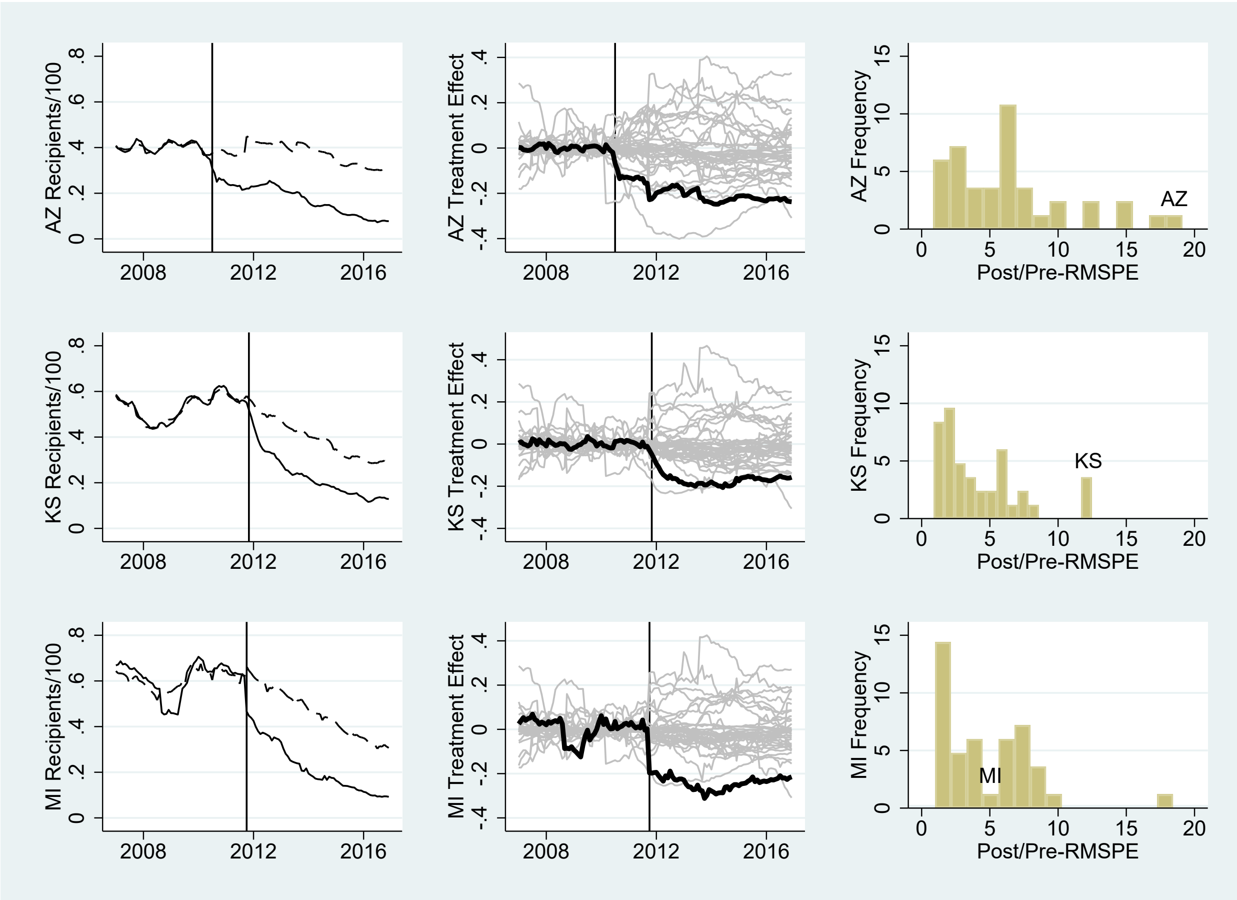
5.2. Results

Figure 2 shows the estimated effect of stricter time-limit policies on monthly adult TANF receipt using the administrative data. (Results using Maine's administrative data are in the online appendix, for reasons discussed in Section 4.) In the upper-left panel of Figure 2, the solid line shows the number of adult TANF recipients per 100 adult residents of Arizona by month. The number of adult TANF recipients per 100 in Arizona hovers around 0.4 before Arizona first shortens its time limit in 2010. After the policy change, the ratio decreases to less than 0.3 and continues to decrease to less than 0.1 by 2016. TANF participation in Arizona and its synthetic control group track each other closely before the policy change and diverge immediately thereafter. After this initial divergence, the vertical distance between Arizona and its synthetic control group remains relatively constant, despite the gradual phase-in of Arizona's 12-month time limit. Table 5 reports $\tilde{\beta}$, the average treatment effect over the posttreatment period. $\tilde{\beta}$ equals –0.198, which constitutes a 49 percent decrease from the baseline mean.

[24]Individual characteristics include age, race, number of children, educational attainment, and the inflation-adjusted maximum refundable EITC benefit by state and family size (Feenberg 2017b).

[25]When I estimate pooled specifications using the ACS data, I limit the sample period to observations up to three years before and up to four years after the (synthetic) policy change to create a balanced panel.

Figure 2: Synthetic Control Estimates of TANF Participation



Synthetic control models using administrative data. The left column displays adults per 100 receiving TANF within each month in analysis states (solid) and their synthetic control groups (dashed). The middle column displays placebo tests for estimated treatment effects of stricter time-limit policies in analysis states. The thick black line represents the analysis state, and the thin gray lines represent control states. The right column displays ratios of post- to pretreatment RMSPE of estimated effects and placebo tests.

Table 5: Effects of Stricter Time Limits on Scaled TANF Participation

Data Method	Admin SCM	Admin DID	ACS DID	ACS Target DID
Arizona	-0.198**	-0.196***	-0.081*	-2.244***
	{0.0263}	(0.0250)	(0.0441)	(0.4692)
	[0.403]	[0.403]	[0.971]	[7.291]
Kansas	-0.168**	-0.236***	-0.321***	-2.514***
	{0.0263}	(0.0280)	(0.0429)	(0.3791)
	[0.514]	[0.514]	[1.221]	[11.506]
Maine			-0.586***	-6.747***
			(0.0481)	(0.4800)
			[2.663]	[23.663]
Michigan	-0.241	-0.304***	-0.307***	-3.430***
	{0.4474}	(0.0553)	(0.0887)	(0.7650)
	[0.600]	[0.600]	[1.723]	[13.830]
Pooled	-0.213**	-0.227***	-0.187**	-2.593***
	{0.0263}	(0.0376)	(0.0892)	(0.6050)
	[0.514]	[0.514]	[1.593]	[11.667]

Estimates of the effects of stricter time limits on TANF participation. Columns "Admin SCM" and "Admin DID" report the effect on the state's number of adult TANF recipients per 100 adults using the administrative data. Column "Admin SCM" contains synthetic control estimates. The ranking of the analysis state's post- to pretreatment RMSPE ratio, relative to those of the placebo treatments, is listed in curly braces. Column "Admin DID" contains difference-in-differences estimates. Columns "ACS DID" and "ACS Target DID" report difference-in-differences estimates of the effects on the percentage of individuals reporting TANF use within the past year, using ACS data. Column "ACS Target DID" restricts the sample to female heads of household aged 18 to 54 with children, no spouse present, and less than a bachelor's degree. "Pooled" lists estimates from specifications in which I pool analysis states. Standard errors are clustered at the state level and listed in parentheses. For each state, pretreatment means through June 2010 are listed in brackets in Columns "Admin SCM" and "Admin DID," and pretreatment means through 2009 are listed in brackets in Columns "ACS DID" and "ACS Target DID." For the pooled analysis, pretreatment means include all pretreatment observations in the balanced panel. Asterisks denote significance at the 1% (***), 5% (**), and 10% (*) levels.

The upper-middle panel of Figure 2 presents placebo-treatment effects. A thin gray line represents each estimated placebo-treatment effect, and the thick black line represents the estimated actual treatment effect, which is simply the vertical distance between Arizona and its synthetic control unit in the upper-left panel of Figure 2. The estimated actual treatment effect is more negative than that of nearly any of the estimated placebo-treatment effects, which implies that Arizona's estimated treatment effect is not simply driven by sampling variation.

The upper-right panel of Figure 2 displays the distribution of the ratios of post- to pretreatment RMSPE across states. Arizona's post- to pretreatment RMSPE ratio is striking: the posttreatment RMSPE is nearly 20 times as large as the pretreatment RMSPE, a greater ratio than that of any control state. Thus, if the time-limit policy change was randomly assigned within the data, the probability of obtaining a post- to pretreatment RMSPE ratio as large as Arizona's is 1/38 = 0.0263. Taken together, evidence suggests that Arizona's stricter time-limit policies caused large and statistically significant decreases in adult TANF receipt.

The middle-left column of Figure 2 shows the estimated effect of stricter time-limit policies in Kansas. The number of adult TANF recipients per 100 adults in Kansas remains at around 0.5 to 0.6 before Kansas first shortens its time limit in 2011. Then, the number of adult TANF recipients per 100 decreases to less than 0.4 and continues to decrease to less than 0.2 by 2016. The TANF participation trajectories of Kansas and its synthetic control group track closely until the policy change, at which time the groups' trajectories diverge. Similar to Arizona, Kansas's initial time-limit policy change in 2011 appears to drive the majority of the effect on TANF participation, despite the state's gradual time-limit phase-in. $\tilde{\beta}$ equals –0.168, which constitutes a 33 percent decrease relative to the baseline mean. The middle-center placebo test panel shows that Kansas's estimated treatment effect is more negative than that of nearly any estimated placebo treatment. Additionally, Kansas's post- to pretreatment RMSPE ratio is greater than that of any control state. Thus, similar to Arizona, Kansas's stricter time limits led to large and statistically significant decreases in adult TANF receipt.

Next, the lower-left panel of Figure 2 shows the estimated effect in Michigan. Michigan's pretreatment TANF participation trajectory does not match that of its synthetic control group as well as those in Arizona and Kansas, which implies that $\tilde{\beta}$ could be inconsistent. Still, when Michigan begins to enforce its time-limit policy in 2011, Michigan and its synthetic control's TANF participation series diverge. As reported in Table 5, $\tilde{\beta}$ equals –0.241, which constitutes a 40 percent decrease relative to the baseline mean, and this effect appears to be immediate. The placebo-treatment graph shows that the estimated actual treatment effect is more negative than that of any placebo-treatment in most posttreatment periods. The lower-right panel of Figure 2, however, shows that 16 control states have a larger post- to pre-RMSPE ratio than Michigan. Given Michigan's relatively large treatment effect, the imperfect fit of Michigan's synthetic control group during the pretreatment period likely drives the low RMSPE ratio.

The remaining columns of Table 5 present difference-in-differences estimates of time-limit effects on TANF participation. Estimates generated using the administrative data tend to be larger in magnitude but are otherwise similar to the synthetic control estimates, which suggests that the difference-in-differences common-trends assumption is reasonable. Consistent with results from the administrative data, all difference-in-differences estimates using the annual ACS data are negative, and most are statistically significant at conventional levels. The statistically significant pooled estimate for all adults implies that stricter time-limit policies decrease annual TANF participation by 12 percent. This effect is practically large but considerably smaller than the statistically significant pooled estimate from the estimated effect using the monthly administrative data, which implies that stricter time limits decrease monthly TANF use by 44 percent. This suggests that stricter time limits may have increased the speed of flows onto and off of the TANF caseload but could also be attributed to differences across datasets.

Estimates within the target subsample are much larger in magnitude than those among all adults. In the pooled analysis, stricter time limits decrease annual TANF participation within the target group by a statistically significant 2.6 percentage points, or 22 percent. The effect-size discrepancy between all adults and TANF-vulnerable women is unsurprising, given that many adults are unaffected by TANF policies.

5.3. Robustness

I test the robustness of results to alternative specifications and include results in the online appendix. First, one may be concerned that models of TANF participation violate the difference-in-differences common trends assumption, given evidence that analysis states changed their time limits in response to the Great Recession's effects on their economies. Because of this, I supplement results from difference-in-differences models using the ACS data with results from weighted difference-in-differences models (Severnini 2014; Spreen 2018; Arkhangelsky et al. 2019; Dickert-Conlin, Elder, and Teltser 2019). In doing so, I aggregate the data to the state level and use all pretreatment values of the TANF participation measure to obtain the synthetic control weight vector. I then disaggregate the data and use the synthetic control weights to estimate Equation (4). Results for all adults are quite similar to those from the baseline difference-in-differences approach. The pooled weighted difference-in-differences estimate (coefficient of –0.214, SE = 0.0730) is slightly smaller in magnitude than the pooled traditional difference-in-differences estimate but is still negative and statistically significant.

I also estimate weighted difference-in-differences models using alternate strategies to obtain the synthetic control weight vector. Because there are not many pretreatment values of the TANF participation measure, I estimate models in which I extend the pretreatment period to begin in 2003. Effects are generally similar under this specification; the pooled coefficient for all adults (coefficient of –0.310, SE = 0.1147) remains negative and statistically significant. Additionally, I estimate models in which I use the average of the lagged TANF participation measure over the pretreatment period, along with covariates, to obtain the synthetic control weight vector as suggested by Kaul et al. (2018). These results are, again, generally consistent with the traditional difference-in-differences estimates; the pooled coefficient for all adults (coefficient of –0.153, SE = 0.0983) is negative but statistically insignificant.

Additionally, it is possible that anticipatory effects of time limits bias results, as in some states policy changes were announced months before they were enacted. I therefore use the administrative data to estimate both synthetic control and difference-in-differences models in which the treatment period begins during the month in which the policy change was first announced. Results from these specifications are nearly identical to those in the main analyses. The pooled estimates using both the synthetic control (coefficient of –0.269) and difference-in-differences (coefficient of –0.222, SE = 0.0361) methods are very similar to those found in Table 5.

Finally, to address concerns that results may be driven by changes in unobserved state TANF policies that are unrelated to time limits, I estimate Equations (2), (3), and (4) without controlling for time-varying state and individual characteristics. Results from these specifications are again quite similar to those found in Table 5.

6. Access to Financial Resources

Given the dramatic decreases in TANF participation shown in Section 5, I now investigate possible implications on access to financial resources via effects on labor supply, income, and participation in other safety-net programs. To do so, I restrict my attention to the ACS subsample of single prime-age female heads of household with children and low levels of education and estimate Equation (4), where Y_{ist} represents the outcome of interest for individual i in state s during year t.

6.1. Results

Table 6 presents estimates of the effects of stricter time limits on annual household TANF, SNAP, and SSI participation and individual work within the past week. (Note that estimates in column "TANF" of Table 6 are simply the estimates in column "ACS Target DID" in Table 5 divided by 100.) Table 6 indicates that stricter time limits are associated with large decreases in SNAP participation. All coefficients are negative, and most are statistically significant at conventional levels. The statistically significant pooled estimate suggests that stricter time limits decrease annual SNAP participation by 6 percent, and the effect size is largest in Maine, which experienced the largest decrease in TANF participation. While point estimates for SNAP participation exceed those for TANF participation, I cannot rule out larger effects of stricter time-limit policies on TANF use than on SNAP use. Decreases in SNAP participation are consistent with loss of categorical SNAP eligibility as individuals become disconnected from TANF.

Table 6: Program Participation and Employment Outcomes among Targeted Individuals

	TANF	SNAP	SSI	Employed
Arizona	-0.022***	-0.023**	-0.010***	0.010**
	(0.0047)	(0.0115)	(0.0028)	(0.0043)
	[0.073]	[0.373]	[0.017]	[0.716]
Kansas	-0.022***	-0.047***	-0.007***	-0.001
	(0.0038)	(0.0088)	(0.0015)	(0.0030)
	[0.115]	[0.354]	[0.025]	[0.764]
Maine	-0.067***	-0.085***	0.005*	0.027***
	(0.0048)	(0.0119)	(0.0025)	(0.0059)
	[0.237]	[0.529]	[0.042]	[0.713]
Michigan	-0.034***	-0.043**	0.014***	-0.031***
	(0.0076)	(0.0160)	(0.0038)	(0.0059)
	[0.138]	[0.500]	[0.032]	[0.698]
Pooled	-0.026***	-0.029**	-0.000	-0.009
	(0.0061)	(0.0128)	(0.0059)	(0.0099)
	[0.117]	[0.451]	[0.022]	[0.713]

Difference-in-differences estimates of the effects of stricter time limits on annual household TANF, SNAP, and SSI use and work within the past week among female heads of household aged 18 to 54 with children, no spouse present, and less than a bachelor's degree using ACS data. The category "Pooled" lists estimates from specifications in which I pool analysis states. Standard errors are clustered at the state level and listed in parentheses. For each state, pretreatment means through 2009 are listed in brackets. For the pooled analysis, pretreatment means include all pretreatment observations in the balanced panel. Asterisks denote significance at the 1% (***), 5% (**), and 10% (*) levels.

While I interpret the effects of stricter time limits on SSI participation with caution because of changes in the costs of obtaining SSI that were unrelated to TANF policies, I find a statistically significant increase in SSI use in Michigan and a marginally significant increase in Maine. The SSI increase in Michigan is especially large; the statistically significant coefficient of 0.014 implies that stricter TANF time limits are associated with a 44 percent increase in SSI use. Negative SSI effects in Arizona and Kansas likely are a function of the Social Security Administration office closures that occurred around those states during the sample period.

Next, I turn to effects of stricter time limits on employment. The statistically insignificant pooled estimate of –0.009 suggests that stricter time limits have virtually no effect on extensive margin employment but masks substantial heterogeneity across analysis states. While extensive margin employment increases by a statistically significant 2.7 percentage points in Maine, stricter time limits have virtually no effect on employment in Arizona and Kansas and decrease employment by a statistically significant 3.1 percentage points in Michigan. I discuss possible channels for heterogeneous employment effects in the next section.

Table 7 presents estimates of the effects of stricter time-limit policies on annual household TANF income, SNAP benefits, and SSI income and individual earned income, EITC benefits, and total resources—posttax income plus SNAP benefits. Unsurprisingly, the effects on TANF benefits are all negative and tend to be statistically significant at conventional levels. The statistically significant pooled coefficient indicates that stricter time-limit policies decrease annual TANF benefits by $113, a 30 percent decrease from the baseline mean.

Table 7: Income Outcomes among Targeted Individuals

	TANF	SNAP	SSI	Earnings	EITC	Total
Arizona	-112***	134***	-70***	-412	51**	-194
	(21)	(46)	(26)	(275)	(20)	(232)
	[256]	[1,496]	[114]	[20,069]	[1,700]	[25,877]
Kansas	-22	-217***	-82***	-377**	35***	-419***
	(13)	(33)	(13)	(155)	(13)	(137)
	[288]	[1,433]	[173]	[19,080]	[2,280]	[25,931]
Maine	-295***	-61	9	1,183***	-229***	433*
	(17)	(44)	(19)	(263)	(24)	(239)
	[715]	[1,559]	[315]	[16,159]	[1,881]	[23,503]
Michigan	-132***	-149***	112***	-583***	19	-656***
	(25)	(52)	(34)	(185)	(34)	(167)
	[459]	[2,032]	[203]	[17,812]	[1,871]	[25,379]
Pooled	-113***	-40	1	-508**	34	-540***
	(25)	(87)	(48)	(191)	(36)	(137)
	[376]	[1,869]	[148]	[18,515]	[1,910]	[25,623]

Difference-in-differences estimates of the effects of stricter time limits on annual household TANF income, SNAP benefits, and SSI income and individual earned income, EITC benefits, and total resources among female heads of household aged 18 to 54 with children, no spouse present, and less than a bachelor's degree, using ACS data. The category "Pooled" lists estimates from specifications in which I pool analysis states. Standard errors are clustered at the state level and listed in parentheses. For each state, pretreatment means through 2009 are listed in brackets. For the pooled analysis, pretreatment means include all pretreatment observations in the balanced panel. Asterisks denote significance at the 1% (***), 5% (**), and 10% (*) levels.

Estimated effects on SNAP and SSI benefits also are generally consistent with estimated effects on SNAP and SSI participation shown in Table 6. SNAP benefit coefficients are negative in all states but Arizona. The statistically insignificant pooled estimate, -40, suggests that stricter time limits decrease imputed annual SNAP income by 2 percent. Average SSI benefits increase by a statistically significant 55 percent in Michigan, consistent with its large increases in SSI participation.

Turning to earnings, the statistically significant pooled estimate suggests that stricter time limits decrease annual earnings by $508, 3 percent of the baseline mean, but earnings effects vary across states, as with the employment effects documented in Table 6. While there is no detectable earnings effect in Arizona, there are statistically significant earnings effects in the other analysis states. Earnings decrease by 2 and 3 percent in Kansas and Michigan, respectively, and increase by 7 percent in Maine. Earnings increases in Maine are consistent with increases in employment but, given their size, probably also are driven by increases in intensive-margin labor supply. Changes in earnings do not tend to have practically large effects on income through imputed EITC benefits. The pooled EITC estimate, 34, is quite small and statistically insignificant.

Finally, while there is no detectable effect of stricter time-limit policies on income after accounting for taxes and SNAP benefits in Arizona, effects are statistically significant at conventional levels in Kansas and Michigan, where time limits decrease total resources by 2 and 3 percent, respectively. Maine, where effects are marginally significant, is the only state in which increased earnings offset decreases in TANF and SNAP benefits. Maine's extensive-margin employment increases likely drive these increases in earnings, at least to some extent.

6.2. Robustness

I test the robustness of results to various sample restrictions and alternative specifications.[26] First, I test whether results are robust to including women aged 15 to 17 and 55 to 59 in the ACS target sample. Including these younger and older women changes results very little. I then test whether restricting the sample to high school dropouts changes results. This sample restriction greatly reduces sample size and increases standard errors while increasing TANF participation effect sizes. Nonetheless, estimates using this sample are generally consistent with baseline estimates. Next, I estimate weighted difference-in-differences models of all financial resource access outcomes, using lagged TANF participation to generate the vector of synthetic control weights. While some of the weighted difference-in-differences results lack the statistical power of the baseline estimates,

[26]Results available upon request.

coefficients generally are similar across specifications. I then estimate specifications in which I do not control for time-varying state and individual characteristics. Results are again similar to the baseline estimates in Tables 6 and 7.

In addition, I test whether demographic changes over the sample period drive the TANF participation effects that I find within the target sample. First, I test whether stricter time limits induce women to migrate out of the analysis states, on the theory that less-generous TANF policies provide an incentive for low-income individuals to migrate to states with more-generous programs. I do not, however, find strong evidence that migration into other states occurs in practice. I also test whether stricter time limits lead to changes in family structure. Bitler, Gelbach, and Hoynes (2006) explain that after their families reach their time limits, children may continue to receive TANF benefits by leaving the household to live with grandparents or other friends or relatives. Nonetheless, I do not find strong evidence that this occurs in practice.

Finally, I estimate the effects of California's stricter time limit for adults only on outcomes related to the access of financial resources. As expected, I find no effect on TANF participation, as children remain eligible for benefits. I do find evidence, however, that TANF income decreases by 9 percent because of the policy change (coefficient of -74, SE = 30), which is consistent with decreased benefits that are due to the removal of parents from the caseload. Decreases in TANF benefits corroborate estimated effects on TANF income from the main analyses.

7. Why Do Effects Vary across States?

There are several possible channels through which labor supply effects could operate to cause the observed differences across analysis states. Differences in TANF work requirements offer one such possibility. As discussed in Section 3, in the absence of binding work requirements, loss of TANF benefits implies increases in labor supply, but when work requirements bind, the theoretical effect of TANF disconnection on labor supply is unclear. Table 2 shows that all analysis states but Arizona implement 30-hour work requirements. Because of this, I study baseline differences in the usual number of hours worked for targeted women who receive TANF relative to women who do not receive TANF. To test for bunching around the work requirement, Table 8 shows the proportion of women in each of these groups who usually work 30 to 32 hours per week, conditional on working, between 2007 and 2009. In each analysis state, the proportion of TANF recipients who work 30 to 32 hours per week exceeds the proportion of nonrecipients who work 30 to 32 hours. This evidence suggests that work requirements bind for at least some TANF recipients. The difference is smallest and statistically insignificant in Arizona, where 15 percent of working TANF recipients usually work 30 to 32 hours but only 8 percent of nonrecipients do so. Still, I fail to reject the null hypothesis that the difference between the proportion of TANF recipients and the proportion of nonrecipients working 30 to 32 hours per week is the same across analysis states, and therefore I cannot conclude that differences in work requirements drive heterogeneous employment effects across states.

Table 8: Proportion Working 30 to 32 Hours per Week in Target Group, Conditional on Employment

	TANF	No TANF	Difference
Arizona	0.153	0.076	0.077
	(0.0467)	(0.0067)	{0.5822}
	111	2,123	2,234
Kansas	0.232	0.076	0.156
	(0.0716)	(0.0113)	{0.0998}
	66	857	923
Maine	0.221	0.106	0.115
	(0.0715)	(0.0201)	{0.0725}
	58	357	415
Michigan	0.206	0.095	0.111
	(0.0292)	(0.0064)	{0.0308}
	332	3,330	3,662

Proportion of working female heads of household aged 18 to 54 with children, no spouse present, and less than a bachelor's degree, who usually work 30 to 32 hours per week. Data was retrieved from ACS years 2007 through 2009 using household weights. Standard deviations and p-values are listed in parentheses and curly braces, respectively, above the number of observations.

Another possibility is that in all states, TANF-vulnerable women increased their labor supply, but that women were unable to find work in states with high unemployment rates. During and after the Great Recession, unemployment rates were high across most states, but Michigan, for example, had a particularly high unemployment rate, 13.7 percent as of 2009. Thus, it is plausible that women in Michigan exhibit similar labor market responses to time limits as women in Maine, for instance, but are unable to secure employment because of insufficient labor demand. To study this possibility, I estimate effects of Missouri's transition from a 60-month to a 45-month time limit in 2016 in the online appendix. Specifically, I use the ACS data, extending the period of study through 2018, to estimate the effect of Missouri's time-limit policy change on financial resource access outcomes among target-sample mothers. In 2016, Missouri's unemployment rate was only 4.6 percent, so increases in employment would suggest that macroeconomic conditions affect the ability of TANF-vulnerable individuals to work more as TANF generosity decreases. In line with this idea, I find a statistically significant 2.3 percentage point decrease in TANF participation (SE = 0.0051) and a statistically significant 4.7 percentage point increase in employment (SE = 0.0040) among women in Missouri. The employment effect in Missouri is even larger than that in Maine and implies that, to some extent, labor demand drives employment responses to stricter time-limit policies.

Differences in TANF policies at baseline suggest that TANF caseload demographics also may play an important role in determining employment effects. Table 2 shows that as of 2009, Maine's TANF program had no time limit, the highest maximum income for eligibility, a relatively generous maximum TANF benefit, and the most generous work exemptions for parents of very young children. Combined with the relatively high levels of TANF participation in Maine shown in Table 4, this suggests that TANF-vulnerable mothers in Maine likely had higher labor market potential than their counterparts in the other analysis states. Tables 3 and 4 provide support for this hypothesis, as target sample mothers from Maine are more similar to welfare recipients as of 1990 than to welfare recipients as of 2009, on several dimensions. Thus, differences in caseload demographics and labor market potential also may drive heterogeneous employment effects of time limit policies.

Finally, the negative total resources effects among target-sample mothers in Kansas and Michigan shown in Table 7 raise the question of how mothers compensate for forgone TANF and earned income. Increases in SSI participation offer one possible channel for this. I find statistically significant increases in SSI income only in Michigan, and increased SSI income does not compensate for forgone earnings and income from other transfer programs. Another possibility is that mothers compensate for decreases in income by relying on transfers from family members or friends. Table 9 displays the proportion of targeted women in analysis states who lived in households in which there was another adult, by employment status and TANF participation before and after their states changed their time-limit policies. Table 9 shows that women who are not employed and do not receive TANF tend to be more likely to live with another adult than any other demographic group.

Furthermore, among women who do not work and do not receive TANF, the proportion living with another adult increases in all of the analysis states after these states shorten their time limits. Kansas and Michigan, where earnings effects are negative and statistically significant, experience the largest increases in the proportion of women living with another adult. Such changes in living arrangements suggest that women who are removed from TANF and do not work may rely on income supports from other household members.

Table 9: Proportion of Targeted Women with Another Adult in the Household

	Before Time Limit Change				After Time Limit Change			
	Employed No TANF	Employed TANF	Not Employed No TANF	Not Employed TANF	Employed No TANF	Employed TANF	Not Employed No TANF	Not Employed TANF
Arizona	0.315	0.258	0.395	0.310	0.357	0.323	0.415	0.468
	(0.012)	(0.046)	(0.026)	(0.057)	(0.009)	(0.034)	(0.018)	(0.051)
	2,117	121	468	93	4,771	288	1,223	156
Kansas	0.274	0.235	0.351	0.158	0.303	0.218	0.414	0.212
	(0.017)	(0.054)	(0.044)	(0.061)	(0.015)	(0.046)	(0.040)	(0.095)
	1,146	91	181	46	1,547	117	293	52
Maine	0.312	0.310	0.379	0.253	0.365	0.324	0.396	0.243
	(0.024)	(0.066)	(0.057)	(0.063)	(0.030)	(0.077)	(0.062)	(0.092)
	582	95	120	83	481	59	116	54
Michigan	0.318	0.230	0.306	0.227	0.314	0.214	0.348	0.258
	(0.009)	(0.022)	(0.021)	(0.028)	(0.008)	(0.023)	(0.017)	(0.033)
	4,440	517	764	303	5,500	472	1,326	326

Proportion of female heads of household aged 18 to 54 with children, no spouse present, and less than a bachelor's degree, who live with at least one other adult. Data was retrieved from ACS years 2007 through 2016 using household weights. Standard deviations are listed in parentheses above the number of observations.

8. Conclusion

In the wake of the Great Recession, states implemented stand-alone TANF policies that created retroactive time limits that became effective immediately. In some cases, these recent time-limit policies were far stricter than time limits that were imposed during welfare reform. Using both administrative and ACS data, I find that the introduction of stricter time-limit policies causes large decreases in TANF participation. When I limit my sample to a group of individuals likely affected by TANF policies, I find that stricter time limits decrease annual household TANF participation by 22 percent. Because TANF interacts with other aspects of the social safety net, I also study the effects of stricter time limits on participation in and income from other transfer programs. I find that stricter time-limit policies decrease annual household SNAP participation by 6 percent. Finally, given TANF labor-supply incentives, I study the effects of stricter time-limit policies on labor supply and find statistically and economically significant increases in employment and earnings only in Maine. Evidence suggests that macroeconomic conditions and the labor market potential of TANF recipients play large roles in determining labor-supply effects of decreased TANF generosity.

Even under very different circumstances, the TANF, SNAP, and SSI participation results that I find are consistent with those of existing literature that estimates the effects of welfare reform. Still, effects on TANF participation are larger than those of much of the previous literature.[27] This likely is due to the retroactive nature of the TANF time-limit policy changes that I study. I show that the recent time-limit policy changes led to large, immediate decreases in TANF participation that, in large part, probably reflected the mechanical effects of losing TANF eligibility. Turning to participation in other safety-net programs, we see that interactions between TANF and SNAP and SSI have not changed over this time, and SNAP and SSI participation results are similar to those of the previous literature.

Nevertheless, under the environment of the 2010s, labor-supply estimates are quite different from those of existing literature. Research using welfare reform to identify the effects of time limits on labor supply finds that time limits unambiguously increase extensive-margin employment.[28] I do

[27]See Grogger and Michalopoulos (2003), Ribar, Edelhoch, and Liu (2008), Chan (2013, 2018), and Low et al. (2018).

[28]See Grogger (2002), Fang and Keane (2004), Swann (2005), Farrell et al. (2008), Fang and Silverman (2009), Mazzolari and Ragusa (2012), Chan (2013, 2017), and Low et al. (2018).

not find this with the 2010s reforms; my findings suggest that TANF work requirements may cause women to work more when they receive TANF than when they are ineligible and no longer required to work. Binding work requirements, decreases in labor demand, and increases in employment among those on the welfare caseload likely lead to contrasting employment and earnings effects between the 1990s and 2010s.

In any event, I study only the short-run effects of TANF time-limit policies. Stricter time limits also may have long-run effects on TANF participation and access to financial resources through both changes in the size and composition of future TANF caseloads and intergenerational income and dependence effects (Hartley, Lamarche, and Ziliak 2017). Future research may address whether the stricter time-limit policies that I study have such long-run effects.

To the extent that income, program participation, and labor supply proxy for access to financial resources, the results that I find imply that policymakers ought to consider macroeconomic conditions and TANF caseload demographics before altering TANF policies such as time limits. While stricter TANF time limits may lead to substantial cost savings for both state and federal governments through decreased TANF and SNAP participation, such changes may substantially reduce the living standards of low-income families. Results suggest that in states without generous TANF programs, welfare recipients exhibit little labor market potential, especially during times of widespread unemployment. Removing such individuals from TANF likely would inhibit their access to financial resources and decrease their overall well-being.

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APPENDIX

1. SNAP Benefits Imputation Procedure

I impute Supplemental Nutrition Assistance Program (SNAP) benefits for households reporting SNAP participation. In order to do this, I make the following assumptions:

- Households take up the standard and shelter cost deductions but no other deductions.
- Households use the standard utility allowance for their shelter deductions.
- Maximum allotments and standard utility allowance calculations in Alaska are slightly imperfect because of geographic data limitations and differences in benefit parameters across regions.
- Monthly income and earnings equal annual income and earnings divided by 12.
- I impute property taxes based on the middle of property tax bins as reported in the American Community Survey (ACS), with the maximum amount being $10,500.
- If a second mortgage payment is listed, I assume that it includes taxes and insurance.
- I assume that all utilities are included in reported rent payments, unless the ACS measure of "gross rent" does not equal the ACS measure of rent.
- Households do not take up the homeless deduction.
- I take weighted averages to adjust fiscal year SNAP parameters for calendar years.

2. Total Resources Imputation Procedure

I generate post-tax income using the TAXSIM program from the National Bureau of Economic Research (NBER). Given data limitations, I must make some assumptions about individuals' income to calculate their taxes. Specifically, I make the following assumptions:

- All of the individual's children in the household (and no others) are dependents.

- A child was younger than age 17 or 18 for the entire tax year if they were younger than that age at the time of the survey.
- The individual does not receive tax benefits related to child-care expenses.
- The individual has no qualified dividends, no long-term capital gains or losses, no property income besides a mortgage, and no mortgage interest. All investment income is in the form of short-term capital gains or losses.
- The individual does not receive unemployment insurance benefits.
- I impute property taxes as in Section A1.

Using these assumptions and the income and demographic data in the ACS, I run NBER's TAXSIM to calculate state and local taxes and subtract these from the individual's total income.

3. Tables and Figures

Table A1: Effects of Stricter Time Limits on Scaled TANF Participation, Including Additional Control States

Method	SCM	DID
Arizona	–0.223**	–0.202**
	{0.0233}	(0.0239)
	[0.403]	[0.403]
Kansas	–0.172*	–0.237***
	{0.0930}	(0.0253)
	[0.514]	[0.514]
Michigan	–0.259	–0.299***
	{0.3721}	(0.0494)
	[0.600]	[0.600]
Pooled	–0.118*	–0.239***
	{0.0698}	(0.0328)
	[0.514]	[0.514]

Estimates of the effects of stricter time limits on the state's number of adult Temporary Assistance for Needy Families (TANF) recipients per 100 adults using the administrative data and including Delaware, Kentucky, Ohio, and Vermont as control states. Column "SCM" contains synthetic control estimates. The ranking of the analysis state's post- to pretreatment root mean square prediction error (RMSPE) ratio, relative to those of the placebo treatments, is listed in curly braces. Column "DID" contains difference-in-differences estimates. Standard errors are clustered at the state level and listed in parentheses. "Pooled" lists estimates from specifications in which I pool analysis states. For each state, pretreatment means through June 2010 are listed in brackets. For the pooled analysis, pretreatment means include all pretreatment observations in the balanced panel. Asterisks denote significance at the 1% (***), 5% (**), and 10% (*) levels.

Table A2: Weighted Difference-in-Differences Estimates of the Effects of Stricter Time Limits on Scaled TANF Participation

	(1)	(2)	(3)
Arizona	–0.113**	–0.087	–0.256***
	(0.0485)	(0.0766)	(0.0482)
	[0.971]	[1.142]	[0.971]
Kansas	–0.247**	–0.244***	–0.283**
	(0.1021)	(0.0705)	(0.0886)
	[1.221]	[1.337]	[1.221]
Maine	0.051	–0.218	–0.189***
	(0.0942)	(0.1594)	(0.0325)
	[2.663]	[2.594]	[2.663]
Michigan	–0.275***	0.061	–0.145
	(0.0627)	(0.0741)	(0.0776)
	[1.723]	[1.717]	[1.723]
Pooled	–0.214***	–0.310***	–0.153
	(0.0730)	(0.1147)	(0.0983)
	[1.593]	[1.592]	[1.593]

Weighted difference-in-differences estimates of the effects of stricter time limits on the percentage of individuals reporting TANF use within the past year, using ACS data. Column (1) presents baseline estimates. Column (2) includes years 2003 through 2016. Column (3) includes controls in the synthetic control model. "Pooled" lists estimates from specifications in which I pool analysis states. Standard errors are clustered at the state level and listed in parentheses. For each state, pretreatment means through 2009 are listed in brackets. For the pooled analysis, pretreatment means include all pretreatment observations in the balanced panel. Asterisks denote significance at the 1% (***), 5% (**), and 10% (*) levels.

Table A3: Effects of Stricter Time Limits on Scaled TANF Participation by Policy Announcement

Method	SCM	DID
Arizona	–0.182*	–0.201***
	{0.0526}	(0.0258)
	[0.406]	[0.406]
Kansas	–0.176*	–0.232***
	{0.0526}	(0.0279)
	[0.513]	[0.513]
Michigan	–0.227	–0.232***
	{0.4737}	(0.0560)
	[0.599]	[0.599]
Pooled	–0.269**	–0.222***
	{0.0263}	(0.0361)
	[0.517]	[0.517]

Estimates of the effects of stricter time limits on the state's number of adult TANF recipients per 100 adults, using the administrative data for which the posttreatment period begins when the policy change is announced. Column "SCM" contains synthetic control estimates. The ranking of the analysis state's post- to pretreatment RMSPE ratio, relative to those of the placebo treatments, is listed in curly braces. Column "DID" contains difference-in-differences estimates. Standard errors are clustered at the state level and listed in parentheses. "Pooled" lists estimates from specifications in which I pool analysis states. For each state, pretreatment means through March 2010 are listed in brackets. For the pooled analysis, pretreatment means include all pretreatment observations in the balanced panel. Asterisks denote significance at the 1% (***), 5% (**), and 10% (*) levels.

Table A4: Effects of Stricter Time Limits on Scaled TANF Participation without Controls

Data Method	Admin SCM	Admin DID	ACS DID	ACS Target DID
Arizona	–0.199*	–0.193***	–0.062**	–0.2060***
	{0.0526}	(0.0181)	(0.0289)	(0.2635)
	[0.403]	[0.403]	[0.971]	[7.291]
Kansas	–0.171**	–0.246***	–0.309***	–2.598***
	{0.0263}	(0.0202)	(0.0296)	(0.2663)
	[0.514]	[0.514]	[1.221]	[11.506]
Maine			–0.567***	–6.249***
			(0.0309)	(0.2903)
			[2.663]	[23.663]
Michigan	–0.242	–0.334***	–0.351***	–3.719***
	{0.4474}	(0.0202)	(0.0296)	(0.2681)
	[0.600]	[0.600]	[1.723]	[13.830]
Pooled	–0.206**	–0.242***	–0.207	–2.822***
	{0.0263}	(0.0376)	(0.1284)	(0.5910)
	[0.514]	[0.514]	[1.593]	[11.667]

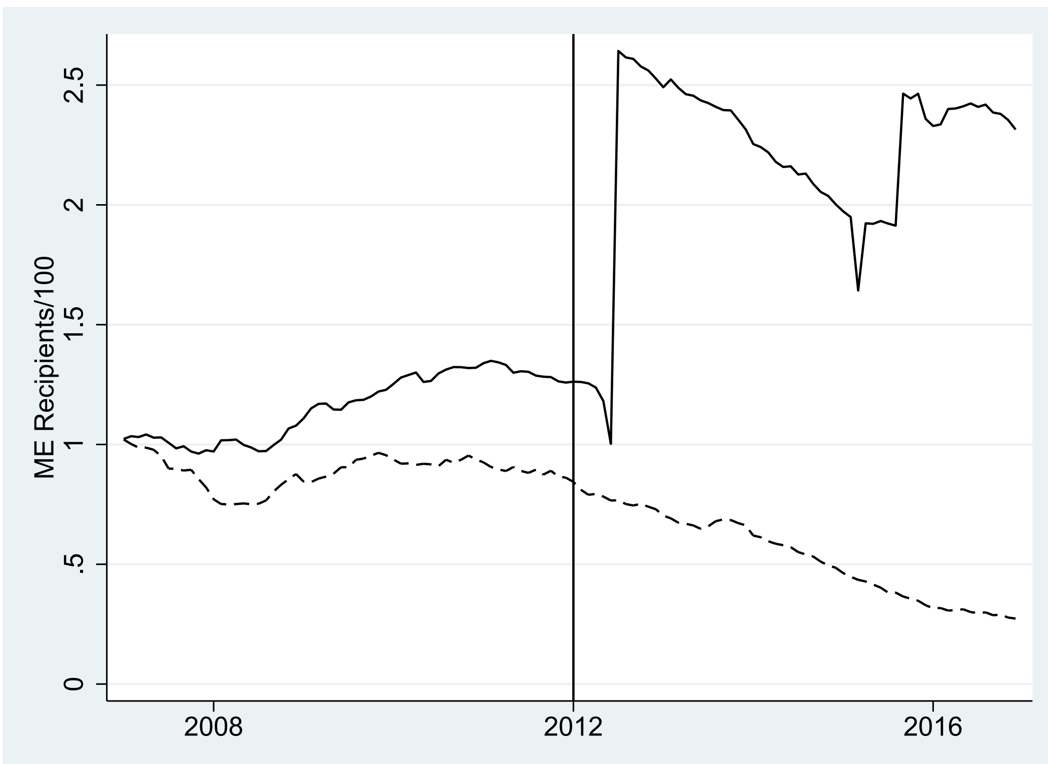
Estimates of the effects of stricter time limits on TANF participation without controlling for time-varying state and individual characteristics. Columns "Admin SCM" and "Admin DID" report the effect on the state's number of adult TANF recipients per 100 adults, using the administrative data. Column "Admin SCM" contains synthetic control estimates. The ranking of the analysis state's post- to pretreatment RMSPE ratio, relative to those of the placebo treatments, is listed in curly braces. Column "Admin DID" contains difference-in-differences estimates. Columns "ACS DID" and "ACS Target DID" report difference-in-differences estimates of the effects on the percentage of individuals reporting TANF use within the past year, using ACS data. Column "ACS Target DID" restricts the sample to female heads of household aged 18 to 54 with children, no spouse present, and less than a bachelor's degree. "Pooled" lists estimates from specifications in which I pool analysis states. Standard errors are clustered at the state level and listed in parentheses. For each state, pretreatment means through June 2010 are listed in brackets in columns "Admin SCM" and "Admin DID," and pretreatment means through 2009 are listed in brackets in columns "ACS DID" and "ACS Target DID." For the pooled analysis, pretreatment means include all pretreatment observations in the balanced panel. Asterisks denote significance at the 1% (***), 5% (**), and 10% (*) levels.

Table A5: Effects of Stricter Time Limits on Financial Resource Access Outcomes in California and Missouri

	TANF	SNAP	SSI	Employed	TANF income	SNAP benefits	SSI income	Earnings	EITC benefits	Total
California	0.001	–0.014	–0.013***	–0.006	–74**	89	–122***	–571*	–189***	–974***
	(0.0071)	(0.0183)	(0.0038)	(0.0048)	(30)	(62)	(36)	(328)	(30)	(269)
	[0.162]	[0.290]	[0.025]	[0.689]	[852]	[1,174]	[227]	[20,544]	[1,533]	[26,587]
Missouri	–0.023***	–0.076***	–0.013***	0.047***	–11	–298***	–112***	1,488***	54**	1,244***
	(0.0051)	(0.0126)	(0.0023)	(0.0040)	(19)	(43)	(20)	(156)	(27)	(139)
	[0.106]	[0.464]	[0.031]	[0.715]	[242]	[725]	[219]	[17,506]	[1,830]	[23,863]

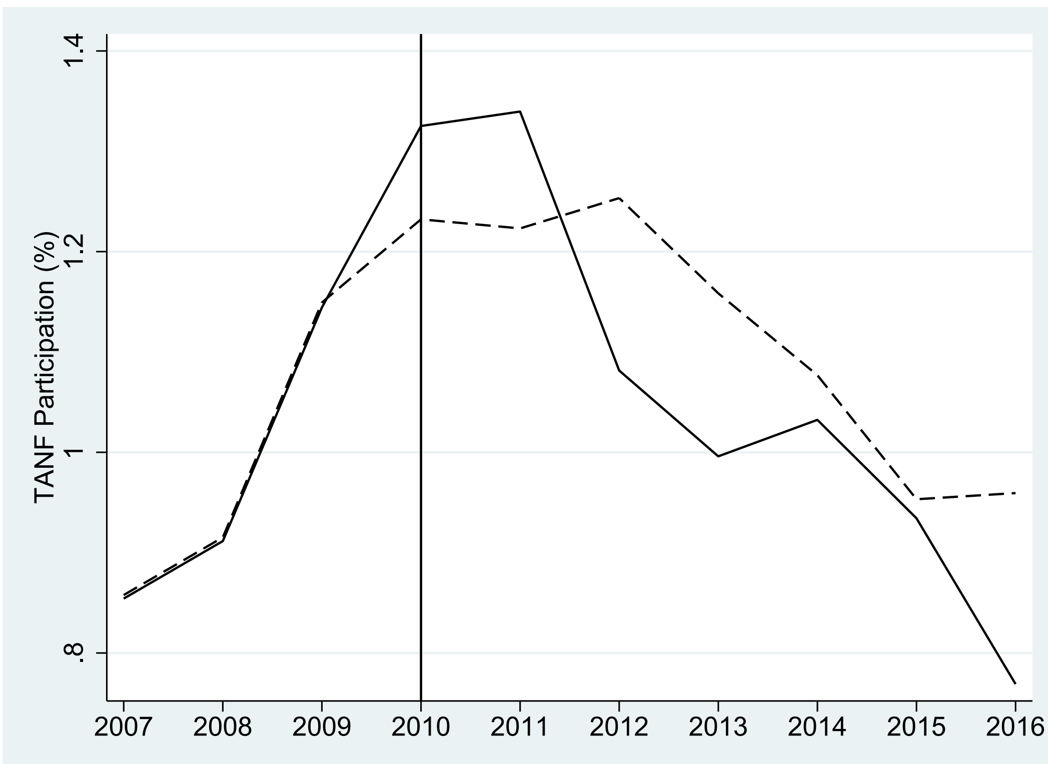
Difference-in-differences estimates of the effects of stricter time limits on annual household TANF use, SNAP use, Supplemental Security Income (SSI) use, TANF income, SNAP benefits, and SSI income and individual work within the past week, earned income, Earned Income Tax Credit (EITC) benefits, and total resources among female heads of household aged 18 to 54 with children, no spouse present, and less than a bachelor's degree in California and Missouri, using ACS data. For Missouri, the period of study extends through 2018. Standard errors are clustered at the state level and listed in parentheses. For each state, pretreatment means through 2009 are listed in brackets. Asterisks denote significance at the 1% (***), 5% (**), and 10% (*) levels.

Figure A1: Synthetic Control Estimates of TANF Participation in Maine



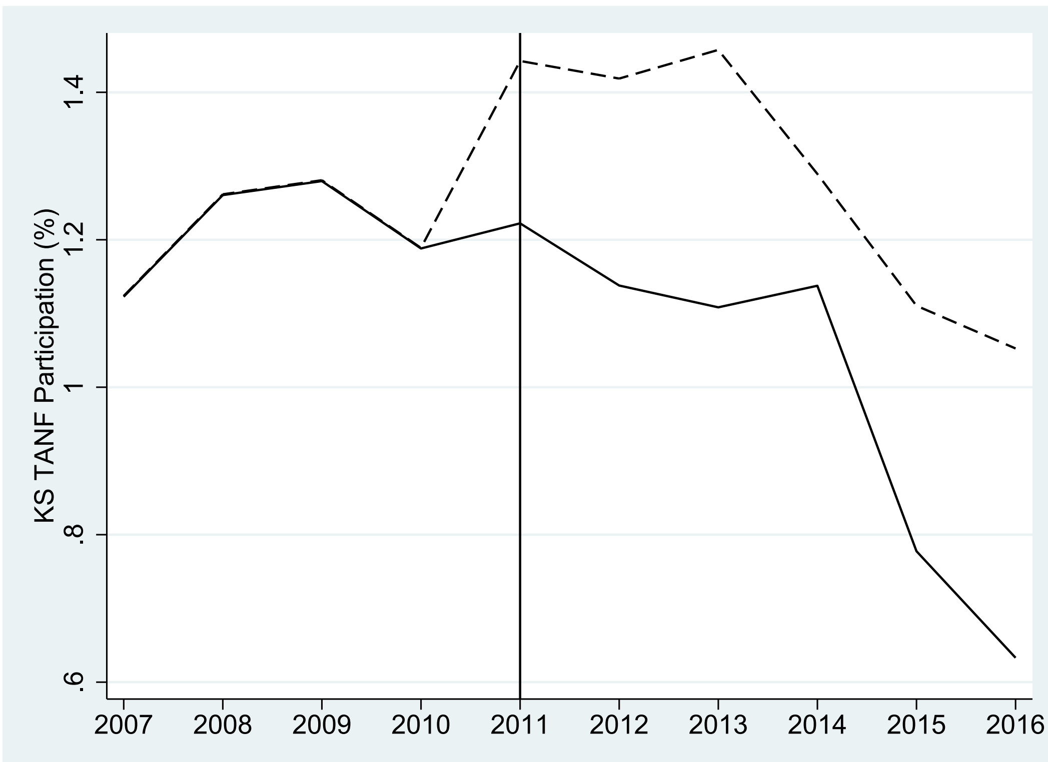
Synthetic control model using administrative data. Adults per 100 receiving TANF within each month in Maine (solid) and its synthetic control group (dashed).

Figure A2: Synthetic Control Estimates of TANF Participation in Arizona Using ACS Data



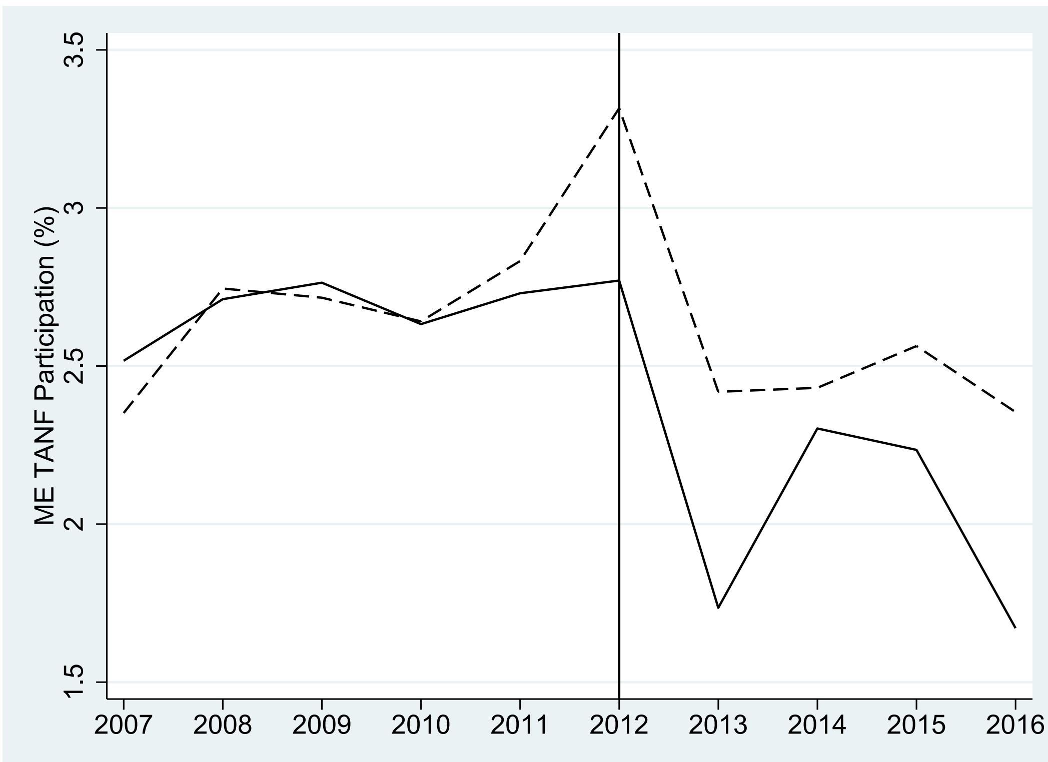
Synthetic control model using ACS data. Percent of individuals reporting TANF use within the past year in Arizona (solid) and its synthetic control group (dashed).

Figure A3: Synthetic Control Estimates of TANF Participation in Kansas Using ACS Data



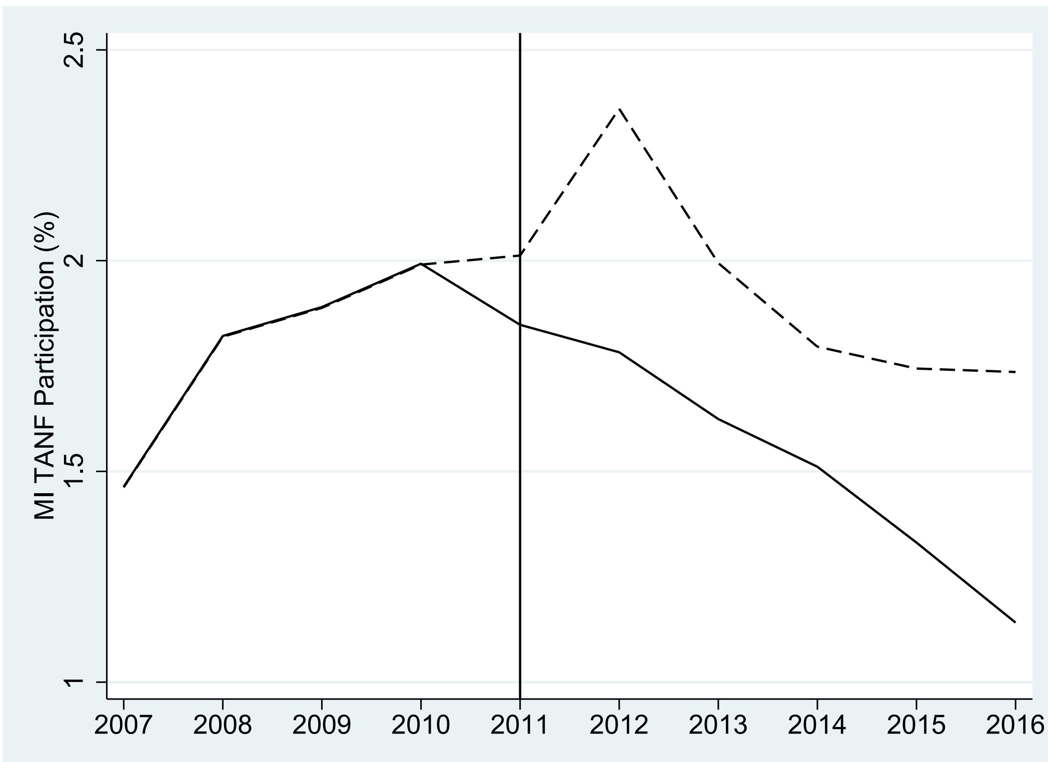
Synthetic control model using ACS data. Percent of individuals reporting TANF use within the past year in Kansas (solid) and its synthetic control group (dashed).

Figure A4: Synthetic Control Estimates of TANF Participation in Maine Using ACS Data



Synthetic control model using ACS data. Percent of individuals reporting TANF use within the past year in Maine (solid) and its synthetic control group (dashed).

Figure A5: Synthetic Control Estimates of TANF Participation in Michigan Using ACS Data



Synthetic control model using ACS data. Percent of individuals reporting TANF use within the past year in Michigan (solid) and its synthetic control group (dashed).