The 1996 Personal Responsibility and Work Opportunity Reconciliation Act (PRWORA) delegated broad authority to the U.S. states over cash assistance programs for low-income families. At the legislation's core was Temporary Assistance for Needy Families (TANF), a block grant program that provides funding to states to combat welfare dependency, support families and children, and prevent out-of-wedlock pregnancies. The creation of TANF and broad delegation of social welfare policymaking authority under the PRWORA prompt two over-arching questions. First, how have states spent TANF funds since the creation of the program? Did states use devolution to reshape welfare spending? And if changes did occur, were there broad trends among states or have states followed distinctive trajectories? Second, why do states spend TANF funds in particular ways? What factors—political, economic, or demographic—account for any observed variation in states' TANF expenditure decisions?

This paper addresses both questions using TANF financial data published by the Department of Health and Human Services' Administration for Children and Families (ACF). The data describe how TANF spending evolved and diversified over time as states shifted funds away from basic assistance payments (i.e. time-limited monthly cash payments that require participants to abide by certain activity and child support requirements) toward work supports, services, and in-kind benefits. With the descriptive analysis in hand, I estimate a fixed effects regression model to examine whether state-level factors can account for the observed variation in state spending patterns between fiscal year (FY) 1998 and 2013. The analysis examines four hypotheses concerning the influence of race and ethnicity, political ideology, economic conditions, and TANF policy factors, and demonstrates that, controlling for national trends, state-level racial, ideological, and economic characteristics significantly correlate with states' cash assistance expenditures.

I

TANF provides each state a capped block grant and the discretion to create its own welfare program for low-income families. States' TANF block grants are neither adjusted for inflation nor, with a few minor exceptions, changes in need.[1] The PRWORA apportioned states' block grants based on the amount of federal funding received by a state for the program that preceded TANF, Aid for Families with Dependent Children (AFDC), and other low-income public assistance programs between FY 1992 and 1995; they range in size from $21.8 million in Wyoming to $3.7 billion in California (Falk 2015). In addition to the federal block grant, the other main source of TANF funding is state-provided Maintenance of Effort (MOE) funds, which are set at 75% of states' FY 1994 contributions to AFDC and other low-income public assistance programs and can increase to 80% if an insufficient number of a state's TANF recipients are engaged in work activities (Falk 2015).

In a particularly broad delegation of authority, the PRWORA empowers states to spend federal and MOE funds in

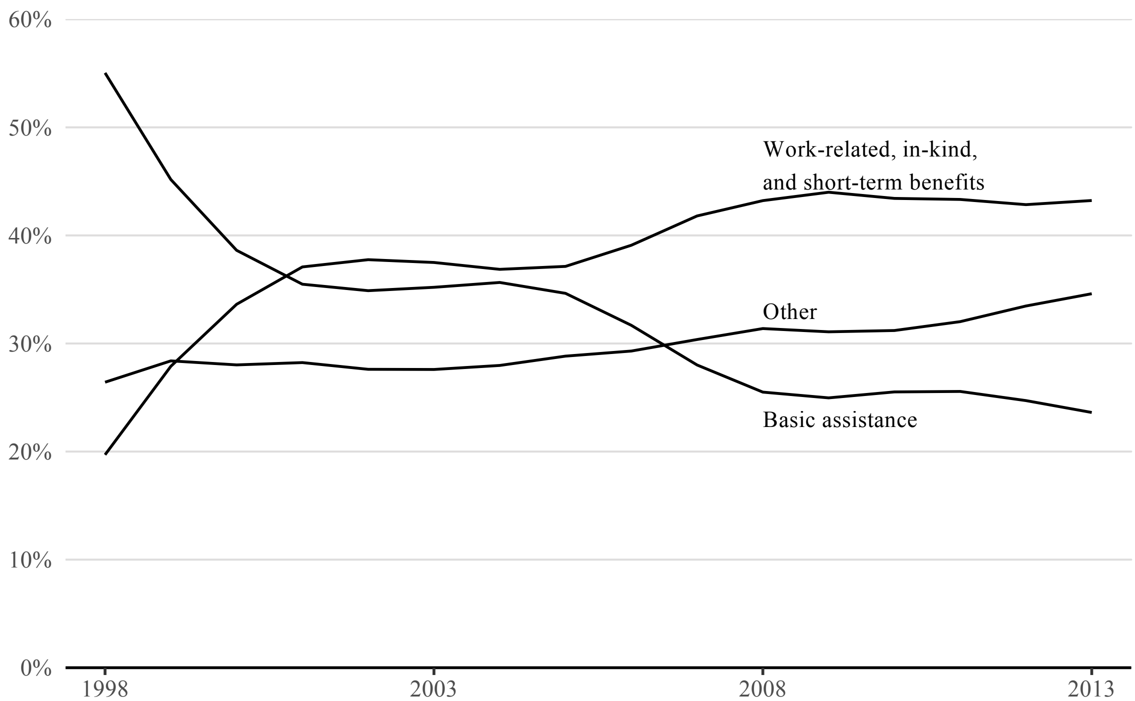
[1] The PRWORA apportioned $2 billion for a contingency fund to support states facing difficult economic conditions and, in order to further aid states during the 2009 recession, the American Recovery and Reinvestment Act allocated $5 billion for basic assistance, emergency assistance, and employment subsidies in FY 2009 and 2010. However, the federal block grant (technically named the State Family Assistance Grant) constitutes the vast majority of federal TANF funding and is not influenced by a state's level of need (Falk 2015).

any manner “reasonably calculated” to realize one of TANF’s four statutory goals: 1) Provide assistance to needy families so that children may be cared for in their own homes or in the homes of relatives; 2) End the dependence of needy parents on government benefits by promoting job preparation, work, and marriage; 3) Prevent and reduce the incidence of out-of-wedlock pregnancies and establish annual numerical goals for preventing and reducing the incidence of these pregnancies; and 4) Encourage the formation and maintenance of two-parent families (“Public Law 104-193” 1996). TANF’s statutory goals allow states to spend TANF dollars on a variety of different programs, benefits, and services, all of which can be classified as either assistance or non-assistance spending. TANF assistance includes basic assistance payments and child care and transportation benefits for families without an employed adult. TANF’s time limits on benefit receipt and activity and child support requirements only pertain to recipients of TANF assistance. States may also spend federal and MOE funds on non-assistance, which includes any other spending justifiable under one of TANF’s statutory goals. Non-assistance spending does not impose federal requirements on states or recipients and includes a broad array of expenditures, including refundable tax credits, work training programs, and family planning services (Falk 2017).

II

For this analysis, I group TANF expenditures into ten spending categories.[2] Figure 1 aggregates those ten categories into three types of spending: basic assistance; work-related, in-kind, and short-term benefits; and other. In FY 1998, on average, a state spent 55.0% of total TANF expenditures on basic assistance and 19.7% on work-related, in-kind, and short-term benefits, with the remaining 26.4% dedicated to other areas, including administrative costs and transfers to other programs.[3] The composition of TANF spending shifted in the years ahead as states decreased the share of TANF funds spent on basic assistance and increased proportional expenditures on work-related, in-kind, and short-term benefits. By FY 2013, the average state spent 23.6% of total TANF spending on basic assistance, a 57.1% decrease from FY 1998, and 43.2% of total TANF spending on work-related, in-kind, and short-term benefits.

[2]See Table 3 in the appendix for category groups.
[3]For more information on “other” spending, see Table 3 in the appendix, Derr et al. (2009), and Office of Community Services (2015).



Note: See Table 3 in the appendix for category groups. Percentages may not add up to 100% in a given fiscal year due to the removal of outlier v
See appendix for more information.

Figure 1: Mean Proportional TANF Spending by Type, FY 1998 - 2013

The over two-fold increase in the average share of TANF funds dedicated to work-related, in-kind, and short-term benefits is shown in more detail in Figure 2, which displays annual proportional expenditures for the spending type's five composite categories. Over time, as states decreased basic assistance spending, they increased the share of funds allocated to a variety of different services and benefits for low-income families. Of the five categories, child care and work-related activities and supports made up the bulk of expenditures in FY 1998 and 2013. However, after a dramatic proportional increase in spending in the late 1990s, spending on both categories was roughly stagnant over the following years and remained below all-time high levels in FY 2013. In contrast, expenditures on marriage and pregnancy programs aimed at supporting healthy marriages and educating families about family planning, refundable tax credits, and diversion benefits (which usually provide one-time lump sum payments to families to help them avoid entering the state's TANF program) consistently increased between FY 1998 and 2013. While the average state spent no TANF funds on any of the three categories in FY 1998, the categories collectively comprised 14.7% of the average state's TANF spending in FY 2013, with marriage and pregnancy programs alone comprising 7.2%.

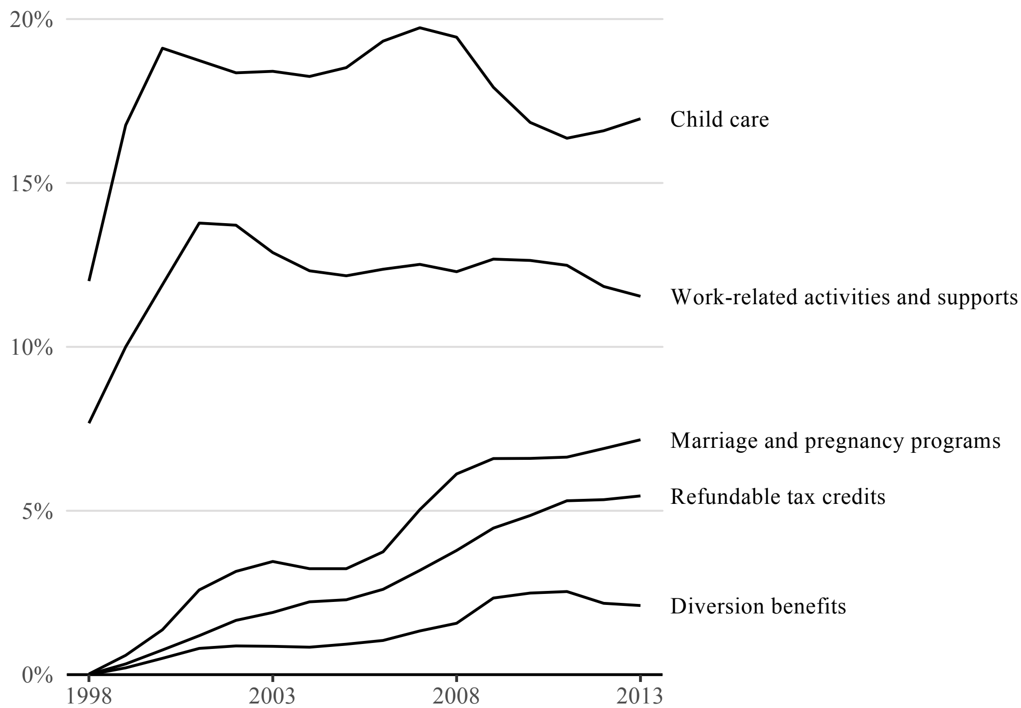


Figure 2: Mean Proportional Expenditures on Work-Related, In-Kind, and Short-Term Benefits, FY 1998 - 2013

The discussion so far has focused on the national shift away from basic assistance spending toward work supports, in-kind benefits and services. While such a focus provides an important aggregated perspective on TANF spending, the PRWORA's broad devolution of policymaking power may have impacted the degree to which a state participated in the national trend of basic assistance retrenchment. In order to more closely examine state-level trends, Figure 3 provides annual boxplots of basic assistance spending.[4] The boxplots show that, as median basic assistance spending decreased, the distribution of state spending remained relatively constant, with annual standard deviations hovering between 10.1% (in FY 2008) and 13.8% in (in FY 1999). Consequently, even states with relatively high levels of basic assistance expenditures reduced cash assistance spending. Of the states that spent the greatest share of TANF funds on basic assistance between FY 2008 and 2013 (i.e. Maine, California, Alaska, and South Dakota), none spent more than the 75th percentile of proportional basic assistance expenditures in FY 1998 (62.6%) and only Maine exceeded the median level of basic assistance spending in FY 1998 (53.1%).

[4]The boxplots in Figure 3 display annual median expenditures (marked by the thick black line) and the first and third quartiles (the upper and lower ends of the "box"). The lines protruding from the boxes equal the distance between the first or third quartile and the value furthest from the respective quartile that does not exceed 1.5 times the difference between the first and third quartiles. Labeled outliers are either greater or less than 1.5 times the difference between the first and third quartiles.

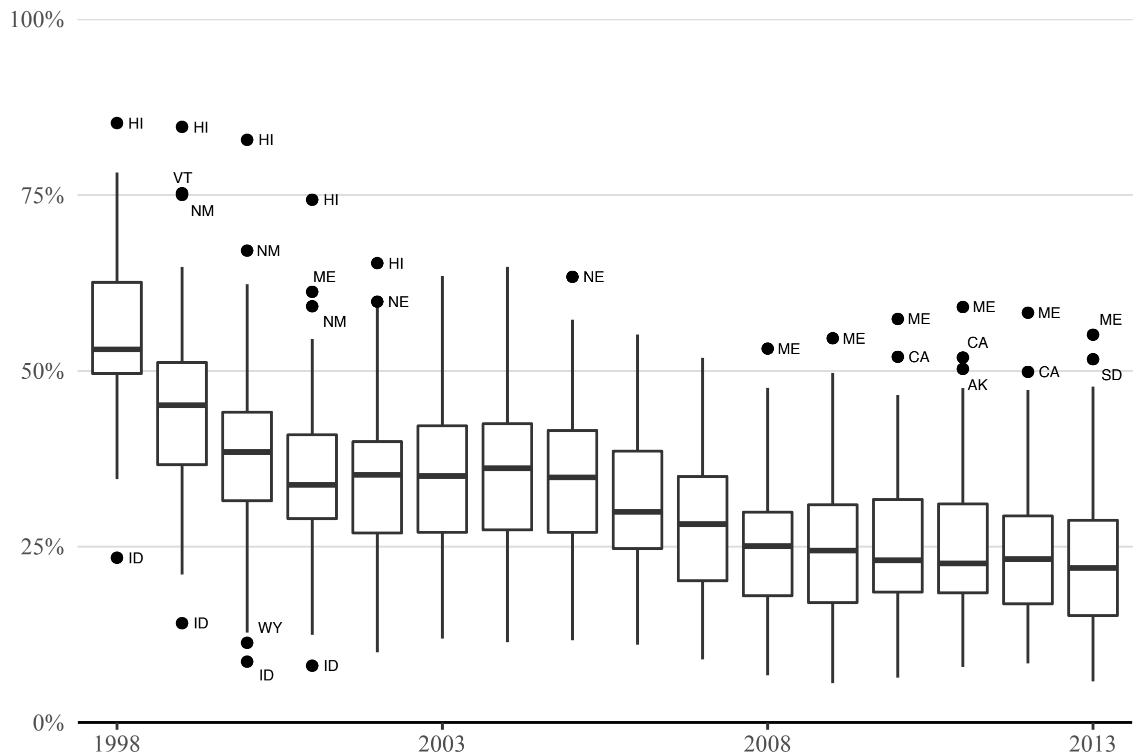
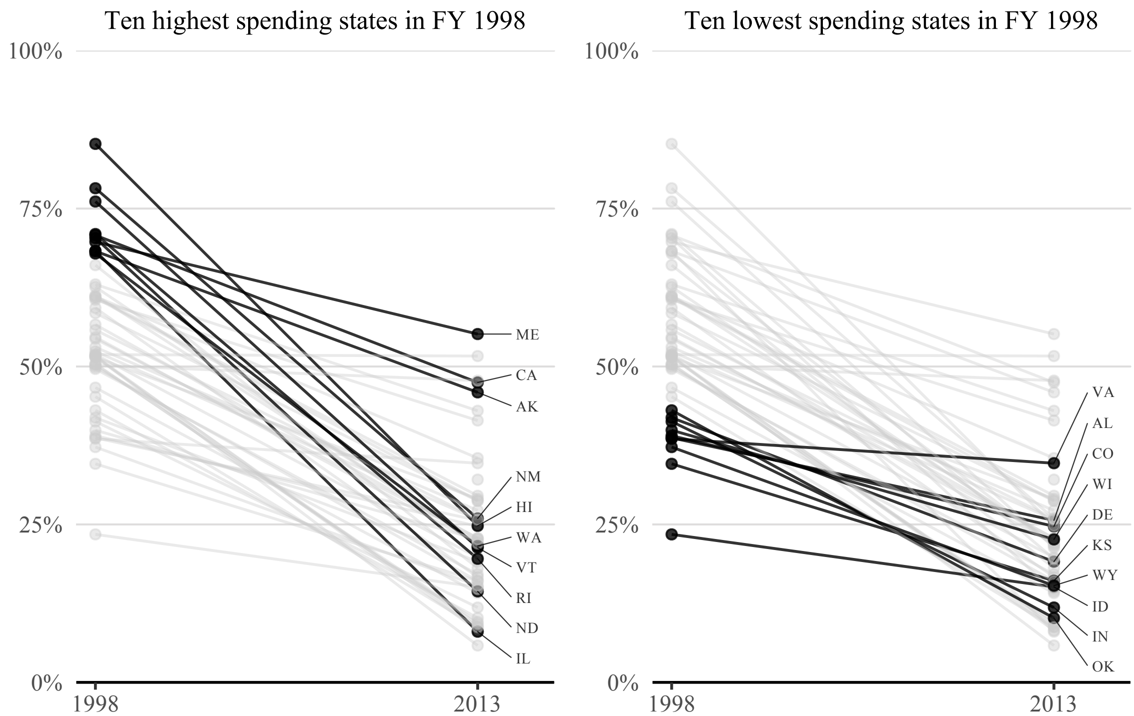


Figure 3: Boxplots of Proportional Basic Assistance Expenditures by State, FY 1998 - 2013

Although the overall variation of the distribution remained relatively constant between FY 1998 and 2013, the relative rank order of states within the distribution was not static. As aggregate basic assistance spending decreased, the relative order of states was reshuffled, with many relatively higher spending states becoming relatively lower spending states and vice versa (Figure 4). For instance, of the ten states that spent the greatest portion of total TANF funds on basic assistance in FY 1998, only three – Alaska, California, and Hawaii – remained among the ten highest spending states in FY 2013. Illinois, another high-spending state in FY 1998, reduced basic assistance spending to such an extent that it was one of the ten lowest spending states in FY 2013. States that spent relatively less on basic assistance in FY 1998 also shifted their spending relative to their peers. Indiana and Oklahoma were the only states to be among the ten lowest spending states in both FY 1998 and FY 2013. On the other hand, Virginia's relatively small decrease in proportional basic assistance spending meant it was among the ten lowest spending states in FY 1998 and the ten highest spending states in FY 2013.



Note: South Carolina and Tennessee removed due to negative reported basic assistance expenditures in FY 1998. See appendix for more information

Figure 4: Proportional Basic Assistance Expenditures in FY 1998 and 2013

III

Since the passage of the PRWORA, states have decreased the share of TANF funds dedicated to basic assistance and increased spending on work-supports, in-kind benefits, and services. However, states did not participate in this national trend in lock-step. Rather, they simultaneously participated in basic assistance retrenchment and altered their spending in distinctive ways. To better understand the variation in states' proportional basic assistance spending, this section examines state-level factors that shaped the degree to which states decreased basic assistance spending. Using a fixed effects regression model that controls for unobserved variation between states and across time, the section demonstrates that states with smaller and more racially diverse TANF caseloads, more conservative state governments, and lower unemployment rates enacted greater reductions in basic assistance spending.

The analysis is based upon four hypotheses concerning states' allocations of basic assistance expenditures: 1) states with more racially and ethnically diverse basic assistance caseloads spend a lower share of TANF funds on basic assistance; 2) states with more powerful and progressive democratic parties spend a greater share of TANF funds on basic assistance; 3) states with more favorable economic conditions dedicate a lower share of TANF funds to basic assistance; and 4) states' basic assistance expenditures are sensitive to programmatic factors, such as caseload levels and work participation rates.

Race and Ethnicity

Two reinforcing strands in the literature on race and social policy are especially significant when considering the potential relationships between race, ethnicity, and states' basic assistance expenditures. The first concerns the role of racial prejudices toward African Americans in shaping public attitudes of welfare recipients. Studies such as Gilens (1996) note the significant effects of white stereotypes of African American mothers on welfare on white Americans' support for welfare assistance. Drawing on national survey data and a randomized experiment, Gilens finds that white Americans that have significantly more negative attitudes toward African American are more likely to oppose welfare programs. Such attitudes translate to opinions of welfare policy, with "racial considerations" serving as "the single most important factor shaping whites' views of welfare" (p. 601).

The other strand of the literature concerns the importance of race in shaping welfare policy outcomes. Several studies have examined the correlations between race and the restrictiveness of states' TANF policies. Soss et al. (2001) note significant positive relationships between the respective proportions of African Americans or Latinos receiving TANF benefits in a state and the probability of a state adopting strong sanctions against participants who do not meet work requirements and a limit on the number of children that can be included in the benefit group (i.e., a "family cap"). The authors also find a significant positive relationship between the share of African Americans in a state's TANF caseload and stricter time limits on benefit receipt. Fellowes and Rowe (2004), in another study, largely echo the conclusions of Soss et al. (2001). They find that, on average, an increase from one standard deviation below the mean percentage of African Americans receiving TANF benefits in a state to one standard deviation above results in significantly stricter TANF benefit eligibility criteria, stricter work requirements, and lower benefit amounts. They also find that the percentage of Latinos receiving TANF benefits is consequential, with an increase from one standard deviation below the mean percentage of Latinos in a state receiving TANF benefits to one standard deviation above resulting in significantly less flexible work requirements but more lenient TANF benefit eligibility criteria.

The literature on race and social policy suggests that race and ethnicity play a role in shaping both negative attitudes toward means-tested assistance and the restrictiveness of specific programs. Consequently, I hypothesize that states with proportionally more Blacks or Hispanics in their TANF caseload spend a lower share of their TANF grants on basic assistance. I test this hypothesis by including as independent variables the percentage of adults in a state's TANF caseload who identify as Black or non-white and Hispanic, respectively.[5]

Partisan Control of State Government

Partisanship and political ideology are often considered crucial factors in structuring the scope and generosity of

[5] Data collected from U.S. Department of Health and Human Services, Administration for Children and Families, Office of Family Assistance: https://www.acf.hhs.gov/ofa/programs/tanf/data-reports.

states' TANF policies, with conservatives generally critical of cash welfare benefits and liberals more supportive of assistance (Rom 1999). The findings of Soss et al. (2001) support the intuitive relationship between TANF policy and ideology. On average, the authors find that a state is 31% more likely to adopt strong sanctions for non-compliant TANF recipients if the state government is one standard deviation more conservative rather than one standard deviation more liberal. Similarly, a state is 9% more likely to adopt strong sanctions, tougher work requirements, narrower time limits, and a family cap if the state government is one standard deviation more conservative rather than one standard deviation more liberal.

I use scores of government ideology to evaluate the relationship between political ideology and basic assistance spending. Originally developed by Berry et al. (1998), the variable captures the ideology of a state government in a calendar year from 0 (most conservative) to 100 (most liberal), weighted by the strength of the Democratic and Republican parties in the upper and lower branches of the state legislature and ideology of the governor. The authors originally measured the ideology of the political parties and governor using interest group ratings, but in Berry et al. (2010) the authors present a slightly different measure of ideology that uses common space coordinates of Congressional roll call votes developed by Poole (1998). Although they correlate strongly, Berry et al. (2010) conclude that the updated measure of ideology is more precise than the original, and it is therefore employed for this analysis.

Quantifying partisan control of state government via a measure of state government ideology controls for changes in party strength and ideology across states and time. Unlike other measures of partisanship, such as party control of state legislatures and governorships, state government ideology does not mask ideological differences between political parties in different states or shifts in political ideology over time. Instead, it incorporates these political differences and evolutions alongside swings in electoral power, creating a nuanced and flexible measure of partisanship. Following the documented relationship between support for welfare and political ideology, I hypothesize that states with higher scores (i.e. more liberal state governments) spend a greater share of TANF funds on basic assistance. Progressive shifts in party ideology and electoral victories by Democratic candidates ought to be commensurate with increased basic assistance spending, reflecting progressive parties' general support of social welfare spending.

Economic Conditions

In addition to race, ethnicity, and partisan affiliation, it is important to consider the effects of state-level economic factors on basic assistance expenditures. The PRWORA was passed in an era of low unemployment, tight labor markets, and rising wages for lower-skilled workers (Blank 2002). In an extensive literature review of TANF and AFDC research in the years following the passage of the PRWORA, Blank (2002) finds five econometric studies arguing that a 1% decrease in a state's unemployment rate correlates with a 5% to 7% reduction in caseload size. Since caseloads are directly related to basic assistance spending (fewer people receiving benefits allows states to spend the funds elsewhere), the studies conducted in the years following the PRWORA's passage imply that state economic conditions ought to bear some impact on basic assistance spending. Qualitative evidence from the economic recession one decade later also supports controlling for state-level economic conditions. Thirty states saw increases in the number of basic assistance recipients following the beginning of the economic downturn in December 2007 (Zedlewski and Golden 2010). As economic conditions worsened, many low-income families sought cash assistance, with likely consequences for basic assistance spending.

I include two economic independent variables in my model: annual state unemployment rates, which I expect to be positively associated with basic assistance spending, and a measure of annual state per capita personal income in thousands of 2013 dollars adjusted for regional differences in purchasing power.[6] I expect per capita income to be inversely related to states' basic assistance spending. Unemployment rates and incomes are likely to be strongly and inversely correlated, but for the population who receives TANF, they may not move in tandem. Moving from welfare to work increases earnings but may decrease assistance benefits. As such, even though the unemployment rate is a common metric of a state's economic vitality (Blank 2002), controlling for unemployment alone may not adequately capture the economic realities of low-income families receiving basic assistance.

In addition to the hypothesized relationships between unemployment, per capita income, and basic assistance spending, economic conditions may also affect TANF spending by exerting fiscal pressures on states. In their study of TANF programs in California, Washington, Michigan, Florida, and Texas, Hahn, Golden, and Stanczyk (2012) note how budget deficits following the economic recession in the 2000s forced some states to reshape TANF spending. TANF's broad spending discretion allows states to shift TANF funds away from basic assistance toward other policy areas previously funded by non-TANF dollars, allowing the latter to be used elsewhere. California, for instance, reduced basic assistance benefits by 8% in 2011 alongside other reductions in job training and child care funding, freeing \$800 million in MOE expenditures for higher education programs. Hahn, Golden, and Stanczyk (2012) find evidence of a similar responses to fiscal pressures in Michigan and Washington. While shifting funds toward other purposes may help states meet budget shortfalls, the authors find that it sometimes also leads to the funding of programs obliquely related to TANF's goals. As an advocate for low-income families in Washington put it when discussing the programs being funded by TANF, "now, no one is pretending that it is for a TANF purpose" (p. 35).

I control for fiscal pressures with a variable that measures states' ending annual fiscal balances and budget stabilization funds (i.e., "rainy day fund") as a percentage of annual expenditures.[7] The hypothesized effect of the variable on basic assistance spending is the opposite of the other economic variables included in the model. As economic conditions worsened, states experienced contradictory pressures. On the one hand, fewer jobs and lower incomes might have led states

[6] Unemployment data collected from the U.S. Department of Labor, Bureau of Labor Statistics: https://www.bls.gov/lau/rdscnp16.htm#data. Nominal per capita income collected from the U.S. Department of Commerce, Bureau of Economic Analysis: https://www.bea.gov/regional/index.htm. Real values calculated using the Consumer Price Index for all urban consumers in, respectively, the Midwest, South, Northeast, and West regions: https://data.bls.gov/cgi-bin/surveymost?cu.

[7] Data collected from the fall editions of the National Association of State Budget Officers's *Fiscal Survey of the States*: https://www.nasbo.org/mainsite/reports-data/fiscal-survey-of-states/fiscal-survey-archives.

to increase basic assistance spending in order to support their residents. At the same time, worsening economic conditions reduced state revenues and strained budgets, perhaps leading to less basic assistance spending as TANF spending was reallocated.

Programmatic Factors

Finally, I hypothesize that program-specific factors such as caseload sizes and work participation rates influence states' basic assistance expenditures. TANF caseloads have decreased in size since the passage of the PRWORA, a continuation of AFDC caseload reductions in the mid-1990s. Between 1998 and 2013, the number of families receiving TANF in an average month decreased by 43.4% from 3.1 to 1.7 million.[8] While changes in caseload sizes are in part, as argued above, a function of economic conditions, they cannot be fully accounted for by economic explanations (Blank 2002). States are not passive actors when it comes to basic assistance eligibility and benefit levels; they control income thresholds, time limits, family cap policies, and work participation requirements – all factors which may impact how many people receive TANF assistance in a state. It is difficult to untangle the specific impact of these policies on caseload sizes and even harder to discern their relationship to basic assistance expenditures given the circularity of program policies and spending. Nevertheless, given the significant decrease in caseloads between 1998 and 2013, it is important to incorporate a broad control for changing caseloads in the model. Hence, I include the annual percentage change in the number of recipients in a state's TANF caseload, including recipients in separate state programs, in an average month.[9]

In addition to accounting for changing caseloads, it is important examine whether work participation requirements influence basic assistance spending. The PRWORA mandated that 50% of all families and 90% of two-parent families receiving TANF assistance in a state be "engaged in work" in a fiscal year in order to avoid a reduction in the state's block grant. Before FY 2007, a state could reduce its required work participation rate by the percentage decrease in its TANF caseload from FY 1995 levels. Since caseloads declined in the years following the passage of the PRWORA, states easily met this requirement. However, the Deficit Reduction Act of 2005 made it more demanding for states to reduce their work participation rates by changing the fiscal year for calculating reductions in caseloads from FY 1995 to FY 2005.[10]

Since 1999 states have also been able to reduce the percentage of their caseload that must meet work requirements by spending more on MOE than mandated by federal statute. But, in addition to caseload reduction credits and excess MOE spending, states can reduce their work participation rate requirement by altering the composition of their TANF caseloads. For instance, a state can reduce the number of unemployed or difficult to employ recipients in the caseload by imposing

[8] Data collected from U.S. Department of Health and Human Services, Administration for Children and Families, Office of Family Assistance: https://www.acf.hhs.gov/ofa/programs/tanf/data-reports.

[9] Data collected from U.S. Department of Health and Human Services, Administration for Children and Families, Office of Family Assistance: https://www.acf.hhs.gov/ofa/programs/tanf/data-reports.

[10] The American Recovery and Reinvestment Act of 2009 suspended states' work participation rate requirements for FY 2009-2011. For more details on what constitutes being "engaged in work" and the changes to work requirement calculations see Falk (2017).

stricter work requirements or eligibility criteria. The resulting caseload is not only more likely to meet the work participation requirement, but also be smaller and have higher earnings, resulting in lower basic assistance expenditures.

A state can also reduce the work participation requirement by increasing the number of employed TANF recipients in the caseload. Some states have taken this approach and offer transitional benefits to TANF recipients who are ineligible due to increased earnings. For example, until October 2015, Michigan granted $10 to former TANF recipients for 6 months after becoming ineligible due to increased earnings if they continued to meet their work requirements. Likewise, in 2016 Missouri gave one-parent families working 30 hours per week after leaving TANF $50 for six months, and New Jersey granted former recipients $200 for 24 months if they continued to work 20 hours per week (Giannarelli et al. 2017; The Urban Institute, n.d.). The benefits allowed states to claim more employed recipients in order to satisfy the work participation rate, with the tangential effect of increasing basic assistance spending.

Since changes in the composition of the caseload in response to the work participation requirement have theoretically ambiguous effects on basic assistance spending, the influence of the work participation requirement on basic spending requires empirical testing. I evaluate the role of the work participation requirement in the model with a binary variable that takes the value of one if a state did not meet its work participation rate.[11]

IV

My dataset includes expenditure data from each state and the District of Columbia between FY 1998 and FY 2013 and the eight explanatory variables described in section III[12] I make the simplifying assumption that every state allocates TANF funds in the year prior to which funds are reported and merge the basic assistance expenditure data with one year lags of the explanatory variables in section III. Table 1 presents linear regression models of states' basic assistance expenditures on the various explanatory variables in 1999, 2005, and 2013. Since each model only includes observations from one year, they cannot exploit year or state fixed effects to remove omitted variable bias. However, they do offer a useful starting point in the analysis by comparing descriptive "snap shots" across three years of data.

[11] Data collected from U.S. Department of Health and Human Services, Administration for Children and Families, Office of Family Assistance: https://www.acf.hhs.gov/ofa/programs/tanf/data-reports.

[12] See appendix for more information on the cleaning process

Table 1: Cross-Section Regression Output

	Dependent variable:		
	TANF funds spent on basic assistance†		
	1999	2005	2013
Percent African American	−.012*	−.008*	−.005
	(.002)	(.002)	(.003)
Percent Hispanic	−.001	.0002	−.001
	(.004)	(.004)	(.005)
Liberalism†	.233*	.137	.040
	(.078)	(.093)	(.069)
Unemployment rate	−.021	.083	.095
	(.046)	(.066)	(.052)
Real per capita income†	1.461*	2.103*	2.075*
	(.378)	(.409)	(.482)
Fiscal balance	.001	.001	.0003
	(.002)	(.004)	(.002)
Caseload size†	1.049*	.864*	.879*
	(.047)	(.061)	(.059)
Work participation rate			.080
			(.151)
Constant	−9.389*	−14.158*	−14.256*
	(3.857)	(4.237)	(5.149)
Observations	48	50	50
R^2	.960	.927	.914
Adjusted R^2	.953	.915	.898
Residual Std. Error	.286 (df = 40)	.351 (df = 42)	.411 (df = 41)
F Statistic	136.453* (df = 7; 40)	76.585* (df = 7; 42)	54.642* (df = 8; 41)

Notes: †variable is logged; observations may be less than 51 due to missing values; *p < 0.05

According to Table 1, in 1999, 2005, and 2013, states' caseloads and per capita incomes are significantly and positively correlated with basic assistance expenditures.[13] In 2013, a state with 1% greater per capita income spends, on average, 2.075% more on basic assistance. Likewise, a state with a 1% larger caseload spends, on average, .879% more on basic assistance. Other coefficients in Table 1 are only significant in 1999 or 1999 and 2005. For instance, in both 1999 and 2005, a state with a TANF caseload composed of 1% more African Americans spends less on basic assistance. In 1999, a state with a 1% more liberal government spends .233% more on basic assistance.

[13] Throughout this paper, I denote statistical significance as $p < .05$.

The cross-sectional linear regression models suggest a number of significant associations between racial, economic, and political variables and states' basic assistance spending. The model containing 1999 data, for example, implies that in the years following the PRWORA, a state with low basic assistance spending is, on average, more conservative and poorer, with a relatively small TANF cash assistance program composed of a relatively high number of African Americans. As shown by the high adjusted R^2 values, the models also capture a wide swath of the variation in basic assistance spending in the respective years. However, the models fall short of describing causal relationships between explanatory variables and basic assistance spending. The lack of time and state controls introduces the potential for bias from unobserved variables, such as political culture or geography, that correlate with the error term and coefficients. Likewise, the cross-sectional models obscure the endogenous relationships between the explanatory variables and basic assistance spending. Caseload sizes are the most problematic instance of this issue. Fewer people in a state's TANF caseload reduces basic assistance spending, which may further reduce caseload sizes. The circularity of the relationship means that states' caseload levels are at least in part a function of basic assistance spending decisions in earlier years. As a result, it is difficult to disentangle whether the coefficient on caseload size is a product of actual changes in states' caseloads or the result of changes in basic assistance spending in earlier years, which may be a function of other factors.

The panel structure of my dataset provides important tools for specifying a model that controls for bias introduced by unobserved phenomena and is free from endogeneity between explanatory variables and basic assistance spending. For one, I can include state and time fixed effects in my model. Intuitively, state-level fixed effects control for unobserved time-invariant differences between states. For instance, perhaps Wyoming's rural geography means that, regardless of the year, economy, or political party in power, the state prioritizes funding transportation programs with TANF funds over basic assistance. By estimating a model that includes a dummy variable for each state in all years, these state-level effects are held constant. Controlling for time effects follows a similar procedure, except the intuition is inverted. By introducing a dummy variable for each year in every state, the panel model controls for factors, such as national developments, that are equivalent in every state but vary across time.

With time and state fixed effects in place, my model can be specified as:

$$Y_{it} = \beta_1 X_{it1} ... \beta_k X_{itk} + \gamma_2 D2_t ... \gamma_{16} D16_t + \alpha_i + u_{it} \tag{1}$$

Where Y is basic assistance spending in state i in year t, $\beta_{1...k}$ measure the correlations between basic assistance spending and the respective explanatory variables $X_{1...k}$ that vary across states and time, $gamma_{2...16}$ capture the effects of the year dummy variables $D2_t ... D16_t$, α is the time-invariant fixed effect for each state i, and u is the error term for each state i in year t. If this model were calculated as it stands, it would likely be biased. The aim of controlling for fixed effects is to reduce omitted variable bias resulting from correlations between the error term and the various explanatory variables. Therefore, by assumption, α_i correlates with $X_{1...k}$. Since the current model retains the fixed effects, it can be thought of as measuring regressing basic assistance spending as a function of the explanatory variables plus an augmented error term equal to the sum of α_i and u_{it}. This error term is necessarily correlated with the explanatory variables, resulting in biased estimates of $\beta_{1...k}$.

First differences and time-demeaning are two methods for transforming equation 1 into an unbiased estimate of states' basic assistance expenditures. The first differences estimator (\ref{FD) removes the time-invariant α_i by subtracting each variable's value in time t from its value in time $t+1$. The resulting model regresses the change in basic assistance expenditures from time t to time $t+1$ on the change in the explanatory variables and time dummy variables from time t to time $t+1$:[14]

$$\Delta Y_{it} = \beta_1 \Delta X_{it1}...\beta_k \Delta X_{itk} + \gamma_3 D3_t...\gamma_{16} D16_t + \Delta u_{it} \tag{2}$$

While first differences removes α_i by subtracting each variable's value in time t from its value in time $t+1$, the time-demeaning estimator (3) eliminates α_i by subtracting each variable's state i mean value from its value in time t. Since α_i is time-invariant, it is eliminated:

$$Y_{it} - \bar{Y_i} = \beta_1(X_{it1} - \bar{X_{i1}})...\beta_k(X_{itk} - \bar{X_{ik}}) + \gamma_2 D2_t...\gamma_{16} D16_t + u_{it} - \bar{u_i} \tag{3}$$

The results of the first differences and time-demeaned estimates of states' basic assistance spending are shown below in the first two columns of Table 2. Both models estimate the expected value of logged basic assistance spending given the various values of the explanatory variables while holding constant time-invariant state fixed effects and national-level time fixed effects. In contrast to the linear models in Table 1, the variable estimating the correlation between caseload size and basic assistance spending is not included due to its endogenous relationship with basic assistance spending.[15] Assuming that the error terms are uncorrelated with the explanatory variables across all years and not serially correlated with each other across time, the first differences and fixed effects models should both be unbiased and consistent, although the fixed effects model would be more efficient [cite (Wooldridge 2015, 472)]. Unfortunately, my dataset meets neither condition. The estimators' different B coefficients imply that bias still exists in the model and a Breusch-Godfrey test suggests that I cannot reject the null hypothesis of uncorrelated errors.

[14] The time index of the first time dummy variable changes from $D2_t$ to $D3_t$ because first differencing eliminates observations from $t = 1$ and including $t = 2$ would result in perfect multicollinearity.

[15] In order to avoid endogeneity between the explanatory variables measuring the percent of African Americans and Hispanics in a state's TANF program, I calculate the variable using the percent distributions of African Americans and Hispanics receiving TANF rather than the logged number of African Americans and Hispanics in the caseload. Including the latter would be problematic as it would vary along with overall changes in caseload sizes, which correlates with basic assistance spending in prior years. It could be argued that unemployment and per capita income also correlate with the error term since they may rise or fall according to basic assistance spending in prior years, but I assume that changes in basic assistance spending do not have a large enough effect on the entire population to sway unemployment levels or incomes.

The first differences and time-demeaned models control for time-invariant and national-level phenomena (in addition to the included explanatory variables), but they do not account for other time-varying state-level phenomena that affect basic assistance spending. Two such potential confounders are caseload sizes and basic assistance spending in prior years. As discussed above, basic assistance spending and caseload sizes are likely circularly related to one another, with decreases in basic assistance spending leading to fewer people receiving basic assistance and further expenditure reductions. This close interrelationship poses problems for explicitly measuring caseload size as an explanatory variable. However, it does provide an opportunity to use states' prior years' basic assistance spending as an instrument to capture the correlation between caseload sizes and basic assistance spending. Estimating a model that includes basic assistance spending in prior years also captures any variation stemming from other state-level forces that vary across time and path dependent allocations of TANF funds.

Table 2: Panel Regression Output

	Dependent variable:		
	TANF funds spent on basic assistance†		
	First differences	Time-demeaned	Lagged dependent variable
Percent African American	$-.006^{*}$	$-.014^{*}$	$-.004$
	(.003)	(.004)	(.003)
Percent Hispanic	.002	.009	.003
	(.004)	(.006)	(.003)
Liberalism†	$.049^{*}$	$.156^{*}$	$.045^{*}$
	(.014)	(.042)	(.016)
Unemployment rate	$-.002$	$-.012$	$-.008$
	(.009)	(.022)	(.007)
Real per capita income†	$-.607^{*}$	$-.686$	$-.553^{*}$
	(.222)	(.790)	(.238)
Fiscal balance	$-.0001$	$-.0002$	$-.001$
	(.0005)	(.001)	(.001)
Work participation rate	$.041^{*}$	$.187^{*}$	$.035^{*}$
	(.013)	(.059)	(.012)
Lagged DV (t - 2)†			$.263^{*}$
			(.072)
Lagged DV (t - 3)†			$-.287^{*}$
			(.043)
Time Fixed Effects	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes
Observations	729	779	593
R^2	.192	.445	.306
Adjusted R^2	.168	.389	.281
F Statistic	8.005^{*} (df = 21; 707)	25.765^{*} (df = 22; 707)	12.578^{*} (df = 20; 572)

Notes: †variable is logged; observations with missing values are dropped; *p < 0.05; standard errors are clustered by state and are robust to serial correlation and heteroskedasticity

Unfortunately, including a lagged dependent variable in a panel model introduces challenges. For one, adding the first period lag introduces bias that increases in severity as t decreases (Nickell 1981), which is especially problematic for my relatively short dataset. The bias can be seen by adding a lagged dependent variable Y_{it-1} to the right-hand side of equation 1 and, as in equation 2, removing α_i by first differencing:

$$\Delta Y_{it} = \rho \Delta Y_{it-1} + \beta_1 \Delta X_{it1} ... \beta_k \Delta X_{itk} + \gamma_3 D3_t ... \gamma_{16} D16_t + \Delta u_{it} \tag{4}$$

The problem lies in the fact that the change in the lagged dependent variable from time $t-2$ to time $t-1$ correlates with the change in the error term from time $t-1$ to time t since Y_{it-1} is partly a function of u_{it-1}. Fully correcting for this error while retaining the benefits of a lagged dependent variable is complex and beyond the scope of this paper.[16] For my purposes, I attempt to remove the bias with the instrumental variable approach suggested by T. W. Anderson and Hsiao (1981) and T. W. Anderson and Hsiao (1982). This technique involves replacing ΔY_{it-1} in equation 4 with ΔY_{it-2} under the simplifying assumption that ΔY_{it-2} is uncorrelated with Δu_{it} but correlated with ΔY_{it-1}. I also include ΔY_{it-3} since it is correlated with basic assistance spending:

$$\Delta Y_{it} = \rho_{t-2}\Delta Y_{it-2} + \rho t - 3\Delta Y_{it-3}\beta_1\Delta X_{it1}...\beta_k\Delta X_{itk} + \gamma_3 D3_t...\gamma_{16}D16_t + \Delta u_{it} \tag{5}$$

The results of equation 5 are displayed above in Table 2. Three explanatory variables remain significant after controlling for basic assistance spending in years $t-2$ and $t-3$: liberalism, per capita income, and whether the state met the work participation rate requirement. The small but significant coefficeint measuring political ideology is in the expected direction, with a 1% increase in state government liberalism corresponding to an increase in basic asssistance expenditures of about .045%. The coefficient capturing the relationship between incomes and basic assistance spending is larger by one order of magnitude. A 1% increase in per capita income correlates with a .553% decrease in basic assistance spending, which conforms with my hypothesis that increasing prosperity within a state leads to less spending on cash assistance.

As discussed above, the influence of the final significant coefficient in the lagged model in Table 2, whether a state met its work participation requirement, is theoretically ambiguous. States can reduce the requirement's burden by either increasing the number of employed recipients through greater basic assistance spending or decreasing the number of unemployed recipients, with the tangential effect of lower basic assistance expenditures. However, as illustrated in the lagged model, the empirical relationship between the work participation requirement and basic assistance spending is clearer: States that did not meet their work participation rate spent apporximately 3.562% more on basic assistance in the following year.[17] Although the the number of states that did not meet the work participation rate in a given year in my dataset is relatively small ($n = 56$), the results still offer evidence that states may have responded to not meeting the work participation rate requirement by bringing more employed TANF recipients into the caseload through expanded eligibility or transitional benefits.

Overall, some of the relatively small coefficients in my models likely in part stem from the lack of sizable variation in the explanatory variables across time. First differencing and time-demeaning only measure intra-state variation, which inhibits the analysis of variables that remain relatively static over time. This problem is compounded in my model by the relative short period under review. Some variables, such as the percent of African Americans and percent of Hispanics in

[16] See Wawro (2002/ed) for a discussion of more advanced techniques for estimating dynamic panel models.
[17] The coefficient is calculated as $(e^{\cdot}035 - 1) * 100 \approx 3.562$.

the caseload, remain fairly constant from one year to the next.[18] As a result, the null results of some variables may be due to the lack of a large enough sample to measure sizable changes in explanatory variables models rather than the actual lack of a relationship between the phenomenon and basic assistance spending.

V

This paper has considered two over-arching questions: How have states spent TANF funds since the passage of the PRWORA and why do states spend TANF funds in particular ways? To answer the first question, I used TANF expenditure data to argue that since the passage of the PRWORA, states have decreased the share of TANF funds dedicated to basic assistance and increased the share spent on other forms of aid, such as child care, marriage and pregnancy programs, diversion benefits, refundable tax credits, and work-related activities and supports. While the shift away from basic assistance was sizable and widespread, with every state participating in retrenchment, I also showed that the rank order of states' basic assistance spending changed over time. The within-distribution variation suggests that state-level factors bore an impact on the degree to which a state participated in the national trend of reduced basic assistance spending.

I utilized the within-distribution variation to approach the second question of why states spent their TANF funds in certain ways. Using four hypotheses to ground my analysis, I estimated a variety of cross-sectional and panel models. I discussed the shortcomings of cross-sectional and static panel models and attempted to estimate a dynamic model that controls for the endogenous relationship between basic assistance spending and caseload sizes as well as the tendency for basic assistance spending levels to correlate from one year to the next. My findings suggest that there are relatively weak relationships between basic assistance spending and both political ideology and whether a state met its work participation rate requirement. I also find a more sizable relationship between basic assistance spending and average income levels, which implies that, holding constant inflation and national-level changes over time, states decrease spending as they become wealthier.

My results also suggest that TANF spending requires further study. While TANF financial data presents challenges, I have implicitly implied throughout this paper (and explicitly argue in the appendix), that the benefits outweigh the costs. Future analyses should use the techniques laid out in Arellano and Bond (1991) and Wawro (2002/ed) to conduct more advanced estimations of the dynamics of basic assistance spending. The data also present the opportunity for various interesting cluster analyses. Observing how patterns of spending across the ten categories of TANF expenditures evolved over time would be useful in itself and likely provoke new questions for causal analysis.

[18] The average state standard deviations of the percent of African Americans in the caseload and percent of Hispanics in the caseload equal 2.91% and 1.78%, respectively.

APPENDIX

From FY 1997 to 2014, states reported federal TANF block grant and MOE spending to the Department of Health and Human Services via the ACF-196 form. The Office of Family Assistance (OFA), an office within the Administration for Children and Families (ACF), oversees TANF expenditure reporting and publishes annual TANF financial reports on its website.[19] The published data from the ACF-196 include federal and state expenditure levels for each state and the District of Columbia across nineteen spending categories. The reporting categories on the ACF-196 did not change between FY 1997 and 2014, providing consistency in the published expenditure data.

The use of the same reporting form and categories caters to researchers interested in TANF expenditure data, but two problems with the ACF-196's structure complicate accurate analysis. First, the form contained broad reporting categories that were too inflexible to accurately trace changes in states' spending over time or compare similar types of spending in different states. Without precise reporting categories, many states struggled to pair new uses for TANF dollars with available reporting categories and consequently reported spending increases in the broadly-defined "other non-assistance" and "assistance under prior law categories" (Derr et al. 2009; Johnson 2013). In other cases, the ACF-196 form's reporting categories lacked clear boundaries, leading states to report similar expenditures in different categories. As the former Director of the OFA noted in regard to the ACF-196, "a state may report TANF spending for pre-school under 'Prevention of Out-of-Wedlock Pregnancies' or 'Other' and possibly even 'Child Care,' although the instructions specifically exclude such expenditures under child care" (Johnson 2013).

Analyzing TANF expenditure data is also complicated by how states reported errors. If a state discovered an error in a prior year's expenditure report, the margin of error was subtracted or added to the respective reporting category on the current year's ACF-196, indistinguishably blurring actual and corrected spending. The negative expenditure values in the published expenditure data are obvious evidence of this accounting method, but such cases are only the ostensible corrections where the margin of error exceeded the actual expenditures in the current year. Any value in the expenditure data can include an upward or downward correction for an error in a prior year's report. Thus, in the words of the former Director of the OFA, it is "impossible to determine the actual TANF expenditures that occur in a fiscal year" (Johnson 2013).

The flaws in the TANF expenditure data are not completely surmountable. It is impossible to know exactly where and when states misreported expenditures or corrected a prior year's expenditure report in a later year's report. Nevertheless, the problems can be mitigated. In order to alleviate the effects of non-mutually exclusive categories, I aggregate the nineteen distinct expenditure categories in the published data into ten using, with a few minor exceptions, the categories already developed by Schott, Pavetti, and Floyd (2015). As can be seen in Table 3, the aggregate categories are composed of

[19] https://www.acf.hhs.gov/ofa/programs/tanf/data-reports.

similar ACF-196 reporting categories, reducing the probability that similar types of spending are treated as distinct in the analysis.

In order to mitigate the effects of corrections for errors in prior year expenditure reports, I create three-year moving averages of the data.[20] The three-year moving averages reduce the short-term variation in spending and prevalence of proportional expenditure values above one or below zero—the ostensible instances of states' correcting prior years' expenditures in the current fiscal year—from seventy-nine to fifty-six. Thus, while an improvement upon the original data, three-year moving averages do not clean all the cases of prior year corrections. Nevertheless, there is a balance to strike between clean and interesting data. Including more years in the average would capture more cases of prior year corrections, but it would also obscure actual changes in spending and inhibit longitudinal analysis.

After synthesizing the original reporting categories into aggregate categories and creating three-year moving averages, my dataset includes expenditures across ten spending categories for every state and the District of Columbia from FY 1998 to 2013 expressed as percentages of total TANF expenditures, where total TANF expenditures equal federal and MOE assistance and non-assistance expenditures plus TANF funds transferred to the Social Services Block Grant and Child Care Development Fund.

[20] All figures in the paper use the averages of the percentages (i.e. the three-year moving average of basic assistance spending divided by total TANF expenditures times 100). Results only change slightly if the moving average is instead calculated as the percentages of the averages (i.e. the three-year moving average of basic assistance spending divided by the three-year moving average of total TANF expenditures, expressed as a percentage). All regression analyses use the logged three-year moving average of basic assistance spending divided by total TANF spending.

Table 3: TANF Spending Categories

Spending Types (used in Figure 1)	Aggregate Categories	ACF-196 Reporting Categories
Basic assistance	Basic assistance	Basic assistance
Work-related, in-kind, and short-term benefits	Child care	Child care (assistance)
		Child care (non-assistance)
		Transfers to the Child Care Development Fund
	Work-related activities and supports	Transportation and supportive services (assistance)
		Transportation (non-assistance)
		Work-related activities and expenses
		Individual development accounts
	Refundable tax credits	Refundable earned income tax credits
		Other refundable tax credits
	Diversion benefits	Non-recurrent short-term benefits
	Marriage and pregnancy	Prevention of out of wedlock pregnancies
		Two-parent family formation and maintenance
Other	Expenditures under prior law	Assistance under prior law
		Non-assistance under prior law
	Other non-assistance	Other
	Administration and systems	Administration
		Systems
	Social Services Block Grant (SSBG)	Transfers to the Social Services Block Grant

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