The Dynamic Effects of Time Limits in Welfare Reform

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Abstract

This paper studies the short and long term effects of welfare time limits on the labor supply, program participation, income and utility of single mothers. Time limits have been extensively discussed by policy makers and analysts, but few formal economic models have been estimated. I estimate a dynamic structural forward-looking model of behavior using monthly panel data from the SIPP combined with the Welfare Rules Database and data on other programs and economic conditions for the years 1996-1999. Time limits accounted for half of the drop in welfare and Food Stamp participation and increased employment slightly during the sample period. There were no overall and distributional effects on income, but much of the impact was 'hidden' as forgone leisure and nonpecuniary benefits of program participation, which I quantify in monetary terms with the equivalent variation measure. There were interesting distributional effects on utility - time limits disfavored strongly against single mothers with high welfare dependence and weakly against those with low wages.

JEL CLASSIFICATION: C15, D61, I38, J16, J22, J31

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1 Introduction

The Temporary Assistance for Needy Families (TANF) program remains one of the most important transfer programs in the United States since its replacement of the AFDC program during the 1996 welfare reform. Time limits are one of the most radical components of the reform to shift single mothers from welfare to work and have received a lot of attention especially at its early stage of implementation. In many states, the typical female-headed family is eligible for at most 5 years of welfare receipt in a time frame of a maximum of 18 years before the child becomes an adult.[1] A research literature has been established to examine widespread concerns that many families would hit the limits quickly, and that some families might be left more disadvantaged even though the policy might effectively encourage work replacing welfare as a major source of income.

Existing studies generally find that time limits played a role in reducing welfare participation and increasing employment shortly before and after the reform.[2] However, few studies focus exclusively on the early post-reform era when time limits were implemented in large scale and when welfare caseload and employment changes were most dramatic. Relatively little is known about the effects of time limits on the earnings, income and utility of single mothers. Few studies use panel data to examine their dynamic response to time limits. In this paper, I attempt to examine the above issues in a unified framework.

I formalize the single mother's joint decision of labor supply, welfare participation and Food Stamp participation in a discrete choice dynamic optimization model. The utility function has a CES form with heterogeneous tastes for work and additive program participation utility costs. It is maximized upon a complex budget constraint with multiple programs and heterogeneous wages. The presence of time limits generates an option value that incurs an additional utility cost of welfare participation each period. The option values depend on the accumulated months on welfare. They are computed directly by backward recursion on a finite horizon and are identified by exogenous variations in time horizon lengths and state time limit policies which determine the dimension of the dynamic optimization problem. The welfare utility cost has a random effects structure to capture individual heterogeneity in 'welfare dependence', which exerts an effect different from

[1] In AFDC, single mothers with children under 18 are usually entitled to benefits if they have low enough income.
[2] Before the reform, time limits were implemented in small scale as part of the 'AFDC waivers'.

state dependence due to time limits. I use monthly panel data from the Survey of Income and Program Participation (SIPP) for the years 1996-1999, and control for economic conditions as well as policy variations using program data from the Welfare Rules Database (WRD) and data on Food Stamp, Earned Income Tax Credit (EITC) and Federal taxes. Then I develop a smoothed frequency simulator and estimate the model structurally with the wage equation with Simulated Maximum Likelihood.

I find that time limits caused around half of the drop in welfare and Food Stamp participation and increased employment slightly during the sample period. Improving economic conditions had a larger effect on employment, and the overall effects of expanded earnings disregards were negligible. There were no overall and distributional effects on income. However, significant 'hidden' utility loss occurred due to forgone leisure and nonpecuniary benefits of program participation, which I quantify in monetary terms with the equivalent variation measure. The deadweight loss due to forgone leisure constitutes around one-fourth of the monetary program benefits. The estimated variance of the welfare utility cost is large, resulting in around 15 percent of the population having nonpecuniary benefits of welfare participation. The overall utility loss is stronger in the long run when single mothers start to hit the limits.

I find significant unobserved individual heterogeneity in the welfare utility cost, which is an important factor in determining who hits the limits. The impacts on time-limit leavers are three to four times larger than on the average population, but they do not respond much until they hit. To study the distributional impacts on utility, I partition the population into subgroups defined by levels of welfare costs and predicted wages respectively. I find that time limits had disproportionately large impacts on single mothers with low welfare costs, but not as much on those with low wages. To re-balance the impacts, less stringent time limits could be implemented among subgroups of the population that are more affected by time limits.

The paper proceeds as follows. Section 2 reviews the literature. Section 3 develops the empirical model. Section 4 describes the data. Section 5 outlines the estimation strategy. Section 6 presents the results. Section 7 concludes. The appendix contains the technical details on estimation and equivalent variation, and a list of commonly used terms used in the literature.

2 Existing Studies on Time Limits and their Limitations

During the massive restructuring of the welfare system in 1996 and 1997, a large number of non-financial rules were introduced aiming to reduce work disincentives and welfare dependence generated by the now-defunct AFDC program.[3] Time limits are arguably the simplest major type of non-financial rule in implementation. Table 1 describes the types of time limits in use, and table 2 shows the time limits in different states. Most states implemented time limits when their state TANF programs began.

As noted in the literature, isolating the effects of time limits is difficult because other policies were often implemented simultaneously, even in policy experiments.[4] U.S. Council of Economic Advisors (1997), Levine and Whitmore (1998) and Ziliak, Figlio, Davis, and Connolly (2000) use state and time variations of the presence of time limits in AFDC waivers and/or TANF[5] with state-level data and find that time limits had a negative effect on AFDC caseload, but results could be sensitive to the years included (Moffitt (1999)). Kaushal and Kaestner (2001) and Meyer and Rosenbaum (2001)[6] use individual-level data and find modest positive effects on employment. All the above studies measure the anticipatory effects of time limits, that is, the change of behavior prior to hitting the limits due to the foreseeing of TANF ineligibility upon hitting. Grogger and Michalopoulos (2003) propose another method to uncover the anticipatory effects. They propose that families with younger children should respond more to the same time limit than families with older children because they have longer eligibility horizons defined as the remaining time until the youngest child turns 18 years of age. In a policy experiment, they find that AFDC participation reduces more for families with younger children. Grogger (2002, 2003, 2004) and Fang and Keane (2004) apply the method above to individual cross-sections for more than ten years through 1999-2002 and find similar results. In particular, Grogger (2004) finds modest positive effect on employment and no significant effects on earnings and income.

In general, the literature lacks a model that explains how single mothers respond dynamically

[3]For a background, see Blank (2000), Moffitt (2003b).

[4]See Moffitt and Pavetti (2000), Bloom and Michalopoulos (2001), Blank (2002), Grogger, Karoly, and Klerman (2002).

[5]U.S. Council of Economic Advisors (1999) combines work requirement and benefit termination time limits.

[6]Meyer and Rosenbaum (2001) combines work requirement and benefit termination time limits.

Table 1: Types of Time Limits

Type of Limit	Description
Lifetime	If received X months of benefits in the past, then ineligible thereafter
Benefit-Waiting	If received X months of benefits in the past, then ineligible for Y consecutive months
Periodic	To be eligible, must have received less than X months of benefits in the past Y months
Reduced-Benefit	If received X months of benefits in the past, then removal of adult's portion of benefits thereafter

to time limits.[7] The method proposed by Grogger and Michalopoulos captures only the individual heterogeneity of responses to time limits (due to differences in eligibility horizons) but not the response of the same individuals over time. In addition, there are two potential econometric problems in existing studies. First, under a time limit, the accumulated TANF usage reflects how close one is to hitting the limit and therefore should affect the probability of TANF participation. Since accumulated TANF usage usually correlates with observable socioeconomic characteristics, omitting this variable, which is often the case in cross-section data, may result in bias.[8] Second, accumulated TANF usage may correlate with unobserved individual heterogeneity in welfare dependence,[9] which itself should be modeled to prevent possible estimation bias.

The economic well-being of single mothers after they hit the limit is mostly unknown as very few of them have hit the limits so far.[10] Farrell, Rich, Turner, Seith, and Bloom (2008) studies these time-limit leavers[11] and finds that they heavily rely on Food Stamp and Medicaid as alternative sources of income after hitting. However, as they note, there are no concurrent control groups to compare with, and direct comparison of the same individuals before and after hitting may be unreliable if socioeconomic variations over time are not controlled. The true impacts can be examined if counterfactuals are constructed from a model.

[7]Swann (2005) imposes time limits in simulation on a dynamic optimization model of work and AFDC participation estimated by pre-reform data. Only the average effects of time limits are reported and no dynamics under time limits are discussed. Bloom, Farrell, and Fink (2002) report dynamic responses in time limit policy experiments, but as they note, results are difficult to interpret because other policy components are also present.

[8]Farrell, Rich, Turner, Seith, and Bloom (2008) are an exception in the literature that use accumulated months on TANF in the analysis of time limits. They obtain this variable from administrative data.

[9]Duncan, Haris, and Boisjoly (2000) shows that the distinction of long- and short-term recipients is important in determining who hits the limits. There is a literature discussing the determinants and measures of welfare dependence. See, for example, Bane and Ellwood (1994), Gottschalk and Moffitt (1994), Moffitt (2002).

[10]U.S. Department of Health and Human Services (2006).

[11]Time-limit leavers refer to those who are forced out of TANF due to time limits. Welfare leaver studies (e.g. Ver Ploeg (2002),Acs and Loprest (2007)) are closely related to studies of welfare dependence and caseload composition. A leaver leaves welfare for various reasons, usually voluntarily. It is generally found that welfare leavers are a more advantageous group in the welfare population and are less dependent on welfare (e.g. Cancian, Haveman, Meyer, and Wolfe (2002),Loprest and Zedlewski (1999)) but it is not always the case (e.g. Moffitt and Stevens (2001)).

Table 2: Time Limit Policies by State

State	Start Date	Type	Length (months)
Alabama	1996/11	Lifetime	60
Alaska	1997/07	Lifetime	60
Arizona	1995/11	Periodic	24 of 60
Arkansas	1997/07	Lifetime	24
California	1998/01	Reduced-Benefit	60
Colorado	1997/07	Lifetime	60
Connecticut	1995/12	Lifetime	21
Delaware	1996/04	Lifetime;Benefit-Waiting	60;48 then 96
DC	1997/03	Lifetime	60
Florida	1996/09	Lifetime;periodic	48;24 of 60
Georgia	1997/01	Lifetime	48
Hawaii	1997/02	Lifetime	60
Idaho	1997/07	Lifetime	24
Illinois	1997/07	Lifetime	60
Indiana	1996/10	Reduced-Benefit	24
Iowa	1997/01	Lifetime	60
Kansas	1996/10	Lifetime	60
Kentucky	1996/11	Lifetime	60
Louisiana	1997/01	Lifetime;periodic	60;24 of 60
Maryland	1996/10	Reduced-Benefit	60
Massachusetts	1996/12	Periodic	24 of 60
Michigan	-	None	-
Minnesota	1998/07	Lifetime	60
Mississippi	1996/10	Lifetime	60
Missouri	1997/07	Lifetime	60
Montana	1997/08	Lifetime	24
Nebraska	1998/01	Periodic	24 of 48
Nevada	1998/01	Lifetime;Benefit-Waiting	60;24 then 12
New Hampshire	1996/10	Lifetime	60
New Jersey	1997/02	Lifetime	60
New Mexico	1997/07	Lifetime	60
New York	1996/12	Lifetime	60
N Carolina	1997/07	Lifetime;Benefit-Waiting	60;24 then 36
Ohio	1996/07	Periodic	36 of 60
Oklahoma	1997/11	Lifetime	60
Oregon	1996/07	Periodic	24 of 84
Pennsylvania	1997/03	Lifetime	60
Rhode Island	1997/05	Reduced-Benefit	60
S Carolina	1997/07	Periodic	24 of 120
Tennessee	1996/09	Lifetime;Benefit-Waiting	60;18 then 3
Texas*	1996/09	Benefit-Waiting	24 then 60
Utah	1997/01	Lifetime	36
Virginia	1997/01	Benefit-Waiting	24 then 24
Washington	1997/08	Lifetime	60
W Virginia	1997/01	Lifetime	60
Wisconsin	1996/10	Lifetime	60

*Source: The Welfare Rules Database. The start dates are the implementation dates for statewide time limits. When there are changes in time limits over time, the latest one is chosen. Maine, North Dakota, South Dakota, Vermont and Wyoming are excluded as they are unidentifiable in SIPP. In the model, Nevada and Tennessee are assumed to follow lifetime limits, while Delaware, Florida, Louisiana and North Carolina follow non-lifetime limits. *Texas has periodic limits of 12,24,36 months of 60 months according to the level of education and work experience.*

3 Empirical Model

3.1 Static Model

The model developed in this paper is a dynamic discrete choice model of utility maximization. It is a straightforward extension of the static model which basically follows Keane and Moffitt (1998) and is described as follows.[12] Consider that in a given month, subject to the budget constraint determined by the wage offer w_i and policy characteristics of transfer programs, the individual i simultaneously chooses the optimal weekly hours of work H_i, TANF participation P_{Ai} and Food Stamp participation P_{Fi}. Following Keane-Moffitt, while the wage affects all her decisions, there are also individually heterogenous taste for work ϕ_{Hi}, TANF participation cost ϕ_{Ai} and Food Stamp participation cost ϕ_{Fi} that affect labor supply and program participation decisions.

Food Stamp is an important source of income for the general low-income population. It is in the model because most recipients of AFDC/TANF automatically get Food Stamp, and it is an important source of income for single mothers who are reaching time limits.[13] Program participation cost is a direct utility loss due to program participation and has been used by many models following Moffitt (1983) to explain the presence of non-participants within the eligible population. It may include stigma and hassle and nonmonetary benefits not captured by the program formula such as peripheral services. The welfare literature finds large participation costs in AFDC and Food Stamp which, in Blank and Ruggles (1996), translates to \$250 and \$140 of benefits respectively for the average eligible non-participant. A constant interactive cost ϕ_{AF} is used to model the relative administrative easiness for TANF participants to obtain Food Stamp but not vice versa.[14]

The benefits are computed from actual program formulas given in the appendix.[15] They vary with family size and are functions of earnings $E_i \equiv w_i H_i$, exogenous non-labor income N_i and program variables.[16] In general, TANF and Food Stamp benefits (B_{Ai} and B_{Fi}) decrease with earnings but the EITC benefit B_{Ei} increases then eventually decreases with earnings. The EITC

[12] The static model is estimated in Chan (2008) using pre-time-limit cross-section data from SIPP.

[13] Multiple receipt of AFDC and Food Stamp has also been studied by Fraker and Moffitt (1988) and Blank and Ruggles (1996).

[14] The estimate of this parameter is crucial in computing the equivalent variation. The Keane-Moffitt model captures the interactive cost as a constant as well but use a different approach.

[15] The same approach is used in Fraker and Moffitt (1988), Keane and Moffitt (1998), Meyer and Rosenbaum (2001).

[16] The food stamp formula is more complex as it depends on TANF benefit.

had become an important transfer program in the mid 1990s. Federal taxes (with payroll tax) B_{Ti} is also included. The static model is:

$$\max_{\substack{P_{Ai}\in\{0,1\},P_{Fi}\in\{0,1\},\\ H_i\in\{0,20,40\}}} (\alpha_i Y_i^{\rho} + (1-\alpha_i)L_i^{\rho})^{1/\rho} + \phi_{Ai}P_{Ai} + \phi_{Fi}P_{Fi} + \phi_{AF}P_{Ai}P_{Fi} \tag{1}$$

$$\text{subject to} \quad Y_i = w_i H_i + B_{Ai}(E_i)P_{Ai} + B_{Fi}(E_i)P_{Fi} + B_{Ei}(E_i) + B_{Ti}(E_i) + N_i \tag{2}$$

$$L_i = 672 - 4H_i \tag{3}$$

$$\alpha_i = \frac{1}{1+\exp(-\phi_{Hi})} \tag{4}$$

The substitutability between leisure and income is determined by ρ and a higher value implies a flatter labor supply curve.[17] When the individual is eligible for welfare because of low earnings, she participates only when the utility gain from program benefits is larger than the utility loss due to participation.[18] The econometric modeling of individual heterogeneity follows Keane-Moffitt:

$$\ln(w_i) = X_{wi}\beta_w + \epsilon_{wi} \tag{5}$$

$$\phi_{Hi} = X_{Hi}\beta_H + \epsilon_{Hi} \tag{6}$$

$$\phi_{Ai} = X_{Ai}\beta_A + \epsilon_{Ai} \tag{7}$$

$$\phi_{Fi} = X_{Fi}\beta_F + \epsilon_{Fi} \tag{8}$$

$X_{wi}, X_{Hi}, X_{Ai}, X_{Fi}$ are observable socioeconomic characteristics for the individual, $\beta_w, \beta_H, \beta_A, \beta_F$ are vectors of coefficients common to all individuals, and $\epsilon_{wi}, \epsilon_{Hi}, \epsilon_{Ai}, \epsilon_{Fi}$ are unobserved heterogeneities assumed to be distributed as multivariate normal with an unrestricted covariance matrix Σ. As in Keane-Moffitt, the parameters are identified through variations in program variables and exclusion restrictions[19] in observable socioeconomic characteristics.

[17]The utility term with leisure and income has a CES utility form and is different from Keane-Moffitt who use a quadratic form. The higher ρ, the 'straighter' are the indifference curves and hence the higher is the substitution effect relative to the income effect. At $\rho = 0$, the utility becomes Cobb-Douglas and both effects cancel, implying a vertical labor supply curve. α_i is the transformed taste for work with value between 0 and 1. The benefits are written as a function of labor supply but are functions of other variables as well.

[18]When the individual is ineligible for welfare, the choice set should be restricted to no-participation but this restriction is not necessary when cost is positive. See Keane and Moffitt (1998) for this technicality.

[19]See Table 5 for the list of exclusion restrictions. Identification of coefficients in the error equations also come from the budget constraint variables. The variance of the work taste error is identified through three levels of observed work. The variances of TANF and Food Stamp cost errors are identified through the joint determination of H_i and

3.2 Dynamic Model of Time Limits

The dynamic model is the static model repeated for multiple periods with intertemporal tradeoffs coming from time limits. Let the eligibility horizon of $T_i + 1$ months be the time horizon, and suppose the single mother maximizes her expected discounted sum of utilities.[20] First, there is an intertemporal constraint (17) about the evolution of the accumulated months on TANF, S_{it}, so that she can keep track of how close she is to hitting the lifetime limit which has length of $\bar{S}_i$ months. TANF participation increases S_{it} by one next period. Since TANF ineligibility upon hitting the limit potentially reduces utilities, TANF participation now potentially decreases the utility stream in the future.[21] Second, assumptions are made about uncertainties in the future. She knows her exact wage, work taste and participation costs in the current period but does not know future $\vec{\epsilon}_{it} \equiv \{\epsilon_{wit}, \epsilon_{Hit}, \epsilon_{Ait}, \epsilon_{Fit}\}$ which are i.i.d. over time but are multivariate normal with covariance matrix Σ in each period. In addition, she thinks the program variables and her socioeconomic characteristics do not change over time. The model is:

$$\max_{\substack{\{P_{Ait}\in\{0,1\},\\ P_{Fit}\in\{0,1\},\\ H_{it}\in\{0,20,40\}|\\ \vec{\epsilon}_{it},S_{it}\}_{t=0}^{T_i}}} E_0 \sum_{t=0}^{T_i} \beta^t \left((\alpha_{it} Y_{it}^{\rho} + (1-\alpha_{it}) L_{it}^{\rho})^{1/\rho} + \phi_{Ait} P_{Ait} + \phi_{Fit} P_{Fit} + \phi_{AF} P_{Ait} P_{Fit} - k P_{Ait} \mathbf{1}(S_{it} = \bar{S}_i) \right) \tag{9}$$

subject to
$$Y_{it} = w_{it} H_{it} + B_{Ai}(E_{it}) P_{Ait} + B_{Fi}(E_{it}) P_{Fit} + B_{Ei}(E_{it}) + B_{Ti}(E_{it}) + N_i \tag{10}$$

$$L_{it} = 672 - 4H_{it} \tag{11}$$

$$\alpha_{it} = \frac{1}{1 + \exp(-\phi_{Hit})} \tag{12}$$

$$\ln(w_{it}) = X_{wi}\beta_w + \epsilon_{wit} \tag{13}$$

$$\phi_{Hit} = X_{Hi}\beta_H + \epsilon_{Hit} \tag{14}$$

$$\phi_{Ait} = X_{Ai}\beta_A + \mu_{Ai} + \epsilon_{Ait} \tag{15}$$

$$\phi_{Fit} = X_{Fi}\beta_F + \epsilon_{Fit} \tag{16}$$

$$S_{i,t+1} = S_{it} + P_{Ait}\mathbf{1}(S_{it} < \bar{S}_i) \tag{17}$$

P_{Ai} and P_{Fi}.

[20] Utilities are discounted by a rate of β per month. The eligibility horizon differ among individuals because the child's age differ. Keane and Wolpin (2002a,b) and Swann (2005) are examples of forward-looking dynamic models of AFDC participation in the literature.

[21] If there are no time limits or if the eligibility horizon is shorter than the time limit length ($T_i + 1 \leq \bar{S}_i$) so that the single mother is not constrained by the limit - see Grogger and Michalopoulos (2003) - decisions made now will not affect the future, so she acts as if she is in a static model, and a dynamic model is unnecessary. Assume $S_{i0} = 0$. Non-lifetime limits are treated as lifetime ones with an adjustment factor in X_{Ai} in the TANF cost equation.

E_0 is the expectation operator at $t = 0$ and $\mathbf{1}(S_{it} = \bar{S}_i)$ is an indicator function that equals one when the individual hits the time limit. k is set to be a large number so that TANF participation is effectively eliminated from the choice set upon hitting the limit. In each month, the optimal choice is conditional upon the value of the S_{it} and realizations of $\vec{\epsilon}_{it}$.

To control for unobserved individual heterogeneity in welfare dependence,[22] the TANF cost equation (15) error has a random effect structure[23] with an unobserved permanent component μ_{Ai} distributed normally among individuals with standard deviation σ_{μ_A} and uncorrelated with other errors in the model. μ_{Ai} is known to the individual as a constant.

3.3 Theoretical and Econometric Implications of Time Limits

To see how the time limit affects current decisions, the model is rewritten in recursive form so that the intertemporal tradeoff can be shown explicitly. The optimal utilities from period $t + 1$ to T_i are represented by the expected value function $E_t V_{t+1}(S_{i,t+1}, \vec{\epsilon}_{i,t+1})$. It is decreasing in $S_{i,t+1}$,[24] meaning that the individual's optimal utility stream is lower when she is closer to hitting the limit, other things unchanged. The optimization problem at t becomes analogous to the static model[25]

$$\max_{\substack{P_{Ait}\in\{0,1\},\\ P_{Fit}\in\{0,1\},\\ H_{it}\in\{0,20,40\}}} (\alpha_{it} Y_{it}^{\rho} + (1-\alpha_{it}) L_{it}^{\rho})^{1/\rho} + \phi_{Ait} P_{Ait} + \phi_{Fit} P_{Fit} + \phi_{AF} P_{Ait} P_{Fit} + \beta E_t V_{t+1}(S_{i,t+1}, \vec{\epsilon}_{i,t+1}) \tag{18}$$

with constraints (10) to (17). TANF participation at t increases $S_{i,t+1}$ and lowers the value function $E_t V_{t+1}$. As noted in the literature, time limits theoretically induce the 'banking up' of welfare for future use through an option value to TANF participation. It can be easily shown that the dynamic model is identical to the static model with the following adjustment in the TANF cost equation:

$$\phi_{Ait} = X_{Ai}\beta_A - \mathcal{O}(t, S_{it}, T_i) + \mu_{Ai} + \epsilon_{Ait} \tag{19}$$

[22] There is a literature about measuring welfare dependence using employment and welfare histories, such as Moffitt (2002) and Ver Ploeg (2002). This approach is not pursued here. See the literature review for more details.

[23] Blank (1989) has used simplified random effects to study the determinants of welfare spell lengths in duration analysis.

[24] This is proven in Chan (2008) and noted separately in Fang and Keane (2004). The model is solved backwards recursively using dynamic programming techniques to obtain the value functions each period.

[25] For simplicity, assume that the time limit is not hit.

where $\mathcal{O}(t, S_{it}, T_i)$ is the option value of 'banking up' one period of TANF defined by

$$\mathcal{O}(t, S_{it}, T_i) \equiv \beta \left(E_t V_{t+1}(S_{it}, \vec{\epsilon}_{i,t+1}) - E_t V_{t+1}(S_{it} + 1, \vec{\epsilon}_{i,t+1}) \right) \geq 0 \tag{20}$$

The time limit increases the TANF cost by the option value, making the individual less willing to participate than without a time limit. In addition, the option value increases with the accumulated TANF usage S_{it} and with the length of the eligibility horizon T_i (Chan (2008)). This implies that, in a reduced form model, the expected signs of the coefficients of S_{it} and T_i on TANF participation P_{Ait} should be negative.

However, existing reduced form studies usually regress TANF participation P_{Ait} on socioeconomic characteristics X_{Ait} and eligibility horizon length T_i (using the age of youngest child), but do not control for accumulated TANF usage S_{it}. After time limits are implemented for some time, S_{it} is likely to diverge among individuals. It will be correlated with X_{Ait} and, in particular, it will be negatively correlated with T_i. Omitting S_{it} will make the absolute values of the estimated coefficients smaller than the true values and underestimate the effects of time limits.

In a reduced form model, omitting the unobserved individual heterogeneity of welfare dependence μ_{Ai} will result in bias as well. S_{it} is positively correlated with μ_{Ai}. If μ_{Ai} is not controlled for, the absolute value of the estimated coefficient of S_{it} will be smaller than the true value so the effect of time limits is underestimated. As μ_{Ai} is unobserved and is correlated with S_{it}, a reduced form model will need to use fixed effects on panel data to produce consistent estimates.

However, in the structural model above, specifying random effects on μ_{Ai} is adequate. This is because the TANF cost ϕ_{Ait} depends directly on the option value but not S_{it}. In particular, the option value is a function of μ_{Ai} and can be computed from the dynamic model for every realization of μ_{Ai}. The relationship between the option value and μ_{Ai} is determined structurally by the dynamic model and does not require fixed effects.

Individual variations in the eligibility horizon and state-level variations in the time limit length generate exogenous individual cross-sectional variations in the option values. In addition, accumulated TANF usage and time generate time-varying option values. These together help identify the effects of time limits through the option values.

4 Data Description

I collect data from the 1996 Panel of the Survey of Income and Program Participation (SIPP), a nationally representative longitudinal survey conducted by the United States Census Bureau with monthly observations of individuals in households from December 1995 to February 2000. The SIPP has been used extensively for studies of the welfare population. The 1996 Panel consists of 12 waves with 4 rotation groups and interviews were given every 4 months. A longitudinal sample of female heads of family with at least one child under 18 is constructed. Individuals who migrated between states, reported severe disability to work, or resided in states not identified by the SIPP [26] are dropped. To reduce computational burden, only individuals with at least 6 observations in the time series are selected. There are 3087 individuals and 87995 observations in the sample.

Monthly participation in TANF and Food Stamp are directly available from the SIPP. All time series start in the months when the time limit policies began. The accumulated months on TANF are computed from monthly TANF participation .[27] The hourly wage and weekly work hours are constructed from event history records and adjustments are made for multiple jobs held and incomplete spells in the month.[28] Workers with less than 35 weekly hours are considered part-time with a value of 20 in the model. The rest of the workers are full-time with a value of 40.

The benefits are computed from formulas in the appendix using program data described below. TANF data are collected from the Welfare Rules Database (WRD) developed by the Urban Institute which contains all financial and non-financial rules in AFDC and TANF in every state since January 1996. Food Stamp, EITC and Federal Tax data are collected from various sources and the programs variables are relatively stable nationwide during 1996-2000. Benefits vary by family size, which is assumed to be the mother plus all her children under 18. The payroll (OASDI) tax is set as 7.65 percent which is half of total. These data are merged with the sample of single mothers by state and month.

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[26] The states not identified by the SIPP are: Maine, North Dakota, South Dakota, Vermont, Wyoming.

[27] When early observations are not available, the independent variables are imputed from averages of the individual to simulate, in the estimation process, the accumulated months on TANF for the first observation of the individual. The imputed months are not used directly in the likelihood function. When observations are not consecutive in the time series, the missing months are imputed in a similar way. There are 8045 imputed months in total.

[28] When the wage is reported, it is used with monthly earnings to derive the weekly hours. For non-hourly paid jobs, the wage is derived from earnings and reported hours. Wages are bottom-coded by $1/hr and top-coded by $40/hr.

The time limit length is collected from the WRD. For states with two time limit policies, the more stringent one is chosen.[29] Reduced-benefit limits do not affect TANF eligibility upon hitting and are treated as no limits. Non-lifetime limits are treated as lifetime ones in the model with an adjustment factor in the TANF cost equation. For example, for a non-lifetime limit with X months then/of Y months, it is assumed that $\bar{S}_i = X$ and the adjustment factor is $\frac{X}{Y}$. The adjustment factor is used in estimation, but in simulation, non-lifetime limits are modeled structurally. The length of the eligibility horizon is computed from SIPP data. It is derived at the time limit policy start date and is the number of months until the average age of children reaches 18.[30]

The socioeconomic variables collected from the SIPP include region, education, age, race, number of children, average age of children, metro residence and exogenous non-labor income. A number of state characteristics are collected from various sources, including the monthly share of employment in the manufacturing sector from the Quarterly Census of Employment and Wages (QCEW), monthly unemployment rate from the Local Area Unemployment Statistics (LAUS), and yearly TANF/AFDC administrative expense per recipient computed from TANF Financial Data and the Green Book.[31] A state TANF sanction policy dummy variable is constructed from the WRD.[32] It equals one when the state has a full sanction, defined as the removal of the entire benefit of the family in the worst case of noncompliance with an activities requirement. State start their sanction policies at different dates, but many start in 1997.

Table 3 shows the descriptive statistics of the major variables. The majority of time series of individuals start in early 1997 and end in mid 1999, spanning an average of 28 months. 80 percent of individuals are subject to a time limit policy, but the time limit length varies with a standard deviation of 17 months. The mean eligibility horizon is around 10 years. It is distributed

[29]In the model, Nevada and Tennessee are assumed to follow lifetime limits, while Delaware, Florida, Louisiana and North Carolina are assumed to follow non-lifetime limits.

[30]Benefits reduce as children reach 18 because the family size shrinks. Although the proper time horizon should be the months until the youngest child reaches 18, the mother would put more emphasis of her actions in months when the family size is large.

[31]These variables are used as exclusion restrictions. QCEW and LAUS are conducted by the Bureau of Labor Statistics. TANF Financial Data is official data collected from states annually by the Department of Health and Human Services and is available from the internet at http://www.acf.hhs.gov/programs/ofs/data/index.html. Details of the construction of the administrative expense variable are given in Chan (2008). The Green Book is U.S. Congress, Committee on Ways and Means (1998).

[32]Individual-level sanction variables are generally difficult to obtain (an exception is Moffitt (2003a)). See Pavetti, Derr, and Hesketh (2003) for a literature review on sanctions.

Table 3: Summary Statistics of Selected Variables

Variable	Mean	Std. Dev.
Demographic Characteristics (by individual):		
South dummy	0.39	-
Years of education	12.15	2.28
Age	33.43	8.77
White dummy	0.71	-
Number of children less than 18	1.76	0.95
Average age of children less than 18	8.32	4.81
Metro residence dummy	0.82	-
Exogenous non-labor income	120.46	381.15
State Level Characteristics:		
Employment share in manufacturing	14.51	4.53
Unemployment rate	4.62	1.00
Annual TANF admin expense per recipient	293.48	192.07
Strict TANF sanction dummy	0.50	-
Budget Constraint Variables:		
TANF benefit standard/maximum*	366.14	168.86
TANF benefit dollar disregards	120.76	126.85
TANF benefit percent disregards	42.89	22.21
Food Stamp benefit standard	295.85	89.46
Time Limit Variables (by individual):		
Time limit dummy	0.80	-
Non-lifetime limit adjustment factor	0.17	0.26
Time limit length in months when any limit	43.35	17.14
Time limit length $>$ eligibility horizon dummy when any limit	0.14	-
Length of eligibility horizon in months	116.01	57.77
Panel Data Characteristics (by individual):		
observations in time series	28.63	9.67
First observation in months from Dec 95	14.41	7.48
Last observation in months from Dec 95	43.11	8.91
Dependent Variables:		
Hourly wage	7.99	7.25
Weekly work hours	25.24	17.01
Weekly earnings	276.27	275.05
Percentage who work	73.49	-
TANF participation rate	12.87	-
Food Stamp participation rate	26.08	-

*Note: Number of individuals = 3087. Number of observations = 87995. * This is the minimum of the benefit standard and the benefit maximum, if the latter exists.*

Table 4: Actual Distributions of Choices

Program Participation	Labor Supply			
Panel 1996-1999, SIPP (sample used in model):				
	No Work	Part-Time	Full-Time	Column Total
No TANF, No Food Stamp	10.9	14.4	47.4	72.7
With TANF, No Food Stamp	0.7	0.3	0.3	1.2
No TANF, With Food Stamp	6.1	4.0	4.2	14.4
With TANF, With Food Stamp	8.8	2.1	0.8	11.7
Row Total	26.51	20.8	52.7	100.0
March 1996, SIPP (for comparison only):				
	No Work	Part-Time	Full-Time	Column Total
No TANF, No Food Stamp	10.6	13.5	41.0	65.1
With TANF, No Food Stamp	1.0	0.2	0.2	1.5
No TANF, With Food Stamp	4.9	3.3	3.8	12.0
With TANF, With Food Stamp	17.2	3.4	0.9	21.5
Row Total	33.8	20.4	45.8	100.0

Note: Full time work is more than 35 weekly hours. The panel sample size=87995. The March 1996 sample size=3639.

quite uniformly, providing considerable variations. 14 percent of individuals subject to a time limit policy are not constrained by it because the eligibility horizon is too short. As in a number of reduced form studies, this forms a source of identification for the effects of time limits. About one-fourth of individuals have participated in TANF for at least one month within the sample period.[33] The manufacturing share and TANF administrative expense tend to increase over time, and the unemployment rate tend to decrease over time. TANF dollar and percent disregards are larger than before the reform, reflecting expanded disregards.

The first part of Table 4 shows the actual distribution of choices in the sample. Most who are off programs work and most who are on programs do not work, but here the skewness is much less extreme than Keane-Moffitt, who use SIPP data in 1984, with a higher proportion of part-time workers and a higher proportion of TANF participants who work. The second part of the table shows the actual choices from a cross section of SIPP just before the welfare reform for comparison purposes. There is an increase in full-time non-participants and decrease in participants of both programs since the reform, but the population 'in the middle' do not change much. This may reflect a tendency in all subgroups of the population towards full-time work and non-participation.

[33]There are 10 percent of them who are on TANF for all observations, and the mean time series length for those who are on TANF all the time is 25 months. The random effect should generate persistence in TANF participation. The empirical model gives 43% of individuals who have ever participated (including the imputed months). However, the dynamic model without random effects (in Chan (2008)) estimates this to be 62%.

5 Estimation Strategy

The parameters estimated from the model include the coefficients $\beta_w, \beta_H, \beta_A, \beta_F$ in the error equations, the utility function parameters ρ and ϕ_{AF}, the covariance matrix of errors Σ, and the standard deviation of the permanent component of TANF cost error σ_{μ_A}. As is the case in other dynamic optimization models, the discount rate is difficult to estimate. The annualized rate is fixed a priori as 0.94 per year.[34] The model is estimated by Simulated Maximum Likelihood (Lerman and Manski (1981)) with 50 draws[35] and technical details are provided in the appendix. There are three nested loops for each individual in each iteration of parameters. The outer loop uses the quadrature method in Butler and Moffitt (1982) with three points of μ_{Ai} to approximate integral of the likelihood with random effects by a weighted sum of likelihoods conditional on μ_{Ai}. In the middle loop, for each μ_{Ai}, the dynamic model is solved backwards recursively once to obtain the option values for all periods t and accumulated TANF usage S. The inner loop computes the reservation values of choices in the model for each t, which depend on the option values, and computes the simulated conditional likelihood in each t using a smoothed frequency simulator of choice probabilities[36] based on the reservation values. The total log-likelihood is the sum of the log-likelihoods of individuals. The standard errors of estimates are obtained by the BHHH algorithm.

Estimation is complicated by the fact that the wage is unobserved for non-workers. The likelihood function is adjusted accordingly as in Keane-Moffitt to estimate the log wage equation together with other error equations structurally in the model. A very small number of individuals with short time limit lengths have observations in the time series with the accumulated months on TANF larger than the limit length, which are probably due to exemption or extension policies[37] or measurement errors. These observations are deleted in estimation.

[34]Since the time series is relatively short, estimation is not likely to be too sensitive to the discount rate within a reasonable range used by the literature. There are studies in the life cycle consumption literature that attempt to estimate the discount rate structurally. For example, Gourinchas and Parker (2002) use the real interest rate to uncover the discount rate.

[35]Lee (1997) discusses the Monte Carlo properties of the SML estimator on long panels and finds that 50 draws are considered adequate for the dynamic models with random effects that he considers. However dynamic optimization models are not discussed in his paper.

[36]The independent variables are in general allowed to vary by t when choice probabilities are computed.

[37]States are allowed up to exempt or exclude 20 percent of cases from time limits with Federal TANF funds. Exemptions or exclusions are usually given to individuals with disabilities or barriers to work. Individuals with reported disability are excluded from the sample.

Table 5: Estimation Results from the Model

	Log Wage Eqn ($\ln w$)	Work Taste (ϕ_H)†	TANF cost (ϕ_A)	FS cost (ϕ_F)
Constant	0.343*	-24.98*	-16.21*	-42.13*
	(0.004)	(0.092)	(1.40)	(0.35)
South dummy	-0.071*	0.71*	-32.91*	1.99*
	(0.001)	(0.021)	(0.56)	(0.09)
Years of education	0.103*	0.71*	-0.72*	-0.86*
	(0.000)	(0.005)	(0.08)	(0.02)
Age	0.014*	0.05*	-2.11*	0.01
	(0.000)	(0.002)	(0.03)	(0.01)
White dummy	0.059*	-0.05	-39.91*	-8.97*
	(0.001)	(0.021)	(0.39)	(0.10)
No. children under 18	-	-0.54*	9.35*	0.25*
		(0.010)	(0.17)	(0.05)
Average age of children under 18	-	0.33*	-1.40*	-0.45*
		(0.003)	(0.05)	(0.01)
Metro residence dummy	0.162*	-	-	-
	(0.001)			
State employment share in manufacturing sector (%)	-0.007*	-	-	-
	(0.000)			
State unemployment rate	-	-0.68*	-	-
		(0.011)		
State annual TANF admin cost per recipient/100	-	-	-3.21*	-
			(0.09)	
State strict TANF sanction dummy	-	-	-23.20*	-
			(0.33)	
Non-lifetime limit adjustment	-	-	16.56*	-
			(1.02)	
Std.dev. of transitory errors σ	0.479*	9.69*	70.73*	34.96*
	(0.000)	(0.020)	(0.24)	(0.11)
Std.dev. of permanent component σ_{μ_A}	-	-	81.37*	-
			(0.27)	
Utility Function Parameters:				
Substitution coefficient ρ	0.65*			
	(0.000)			
Interactive participation cost ϕ_{AF}	90.18*			
	(0.31)			
	Correlation Matrix of Errors:			
	ϵ_H	ϵ_A	ϵ_F	
ϵ_w	-0.05*	0.19*	0.16*	
	(0.002)	(0.003)	(0.002)	
ϵ_H	-	-0.03*	-0.14*	
		(0.002)	(0.002)	
ϵ_A	-	-	-0.81*	
			(0.002)	

Note: Simulated Log Likelihood = -178000. Standard errors are in parentheses. Number of individuals = 3087. Number of observations = 87995. Number of draws = 50. †All values of estimates and standard errors are multiplied by 10.
** Significant at the 1 percent level.*

Table 6: Estimated Observed and Unobserved Heterogeneities in the Error Equations

	Log Wage ($\ln w$)	Work Taste (ϕ_H)	TANF cost (ϕ_A)	FS cost (ϕ_F)
Means of Predicted Values	2.11(8.24)	-1.59(0.17)	-148.29	-61.12
Std. Dev. of Predicted Values	0.30(2.51)	0.29(0.04)	35.43	5.44
Std. Dev. of Transitory Errors	0.48(4.11)	0.97(0.14)	70.73	34.96
Std. Dev. of Permanent Component	-	-	81.37	-

Note: At the means, the wage w is \$8.24/hr, and the transformed work taste α is 0.17. The figures in brackets in the next two rows are the approximate standard deviations of w and α respectively. Number of individuals = 3087.

6 Results

6.1 Basic Estimation Results

The estimates of the model are shown in table 5. Most of the coefficient estimates are statistically significant[38] and have expected signs. Single mothers who are white, older and have more education have higher wage, work taste, TANF cost. Residence in the south reduces wage but increases work taste and TANF cost.[39] Having more and younger children decreases work taste, TANF cost and Food Stamp cost. High unemployment results in low work taste, indicating higher implicit cost in finding work. Sanctions increase TANF cost due to higher implicit cost to enter TANF or easier forced exits. Non-lifetime limits are less stringent than lifetime limits of equal length.[40]

Table 6 computes the predicted values of the log wage, work taste, TANF cost and Food Stamp cost using socioeconomic variations among individuals.[41] At the mean, the wage offer is \$8.24 per hour, and the weekly work hours would be (roughly) 28 hours if there were no transfer programs.[42] The TANF cost is substantially higher than that of Food Stamp, which is consistent with Blank

[38] The small standard errors are probably partly due to numerical instability in estimating random effects from long panels using simulation and quadrature methods. Chan (2008) tests variations of the model without random effects. Standard errors become larger, but the estimates appear stable and give roughly the same types of statistical implications. In addition, he finds that the standard errors are only slightly affected by the model specification of dynamic optimization.

[39] Some coefficients in the Food Stamp cost equation do not have expected signs but Table 6 shows that observed variations of Food Stamp cost are very low.

[40] Residence in metro areas and in states with a small manufacturing sector result in higher wage. Residence in states with high TANF administrative cost results in high TANF cost, suggesting stricter screening by the administration.

[41] Predicted values in error equations are analyzed with normal probability plots. The work taste and TANF cost resemble normal distributions, while log wages are more concentrated in the center than a normal distribution. The Food Stamp cost tends to be bimodal.

[42] At the mean, the transformed work taste is $\alpha = 0.17$, which is roughly the optimal share of maximum monthly income without any transfer programs and non-labor income. The maximum monthly income is $8.24 * 672 = 5537$. The optimal share of work per week is $168 - (1 - 0.17) * 5537/(8.24 * 4) = 28$.

Table 7: Work Reservation Wages by Taste for Work and Non-Labor Income

Weekly Work Hours	Low Work Taste		Mean Work Taste		High Work Taste	
	$N = 0$	$N = 120$	$N = 0$	$N = 120$	$N = 0$	$N = 120$
0 and 20	\$8.76	\$11.71	\$1.92	\$3.38	\$0.42	\$1.09
20 and 40	\$21.43	\$21.95	\$4.71	\$5.18	\$1.04	\$1.38

Note: Substitution coefficient $\rho = 0.65$. Results are shown with cases -1,0,+1 standard deviations away from mean work taste ϕ_H. N is monthly exogenous non-labor income. The budget constraint is assumed without transfer programs.

and Ruggles (1996). The TANF cost varies much more than the Food Stamp cost in terms of observed and unobserved heterogeneities. These imply that Food Stamp is a more generic transfer program where participation depends largely on financial status, while TANF may have different rules targeting different populations resulting in large variations of participation cost. Around 15% of the population have negative cost for TANF, which is plausible because depending on the state program, TANF may entail services such as training and extra financial incentives to increase work.[43] Around 5% of the population have negative cost for Food Stamp.[44] The permanent component constitutes half of the unobserved heterogeneity of the TANF cost, implying that there are large variations of unexplained welfare dependence in the population.[45]

The estimated correlation matrix of errors is generally weak. However, σ_{AF} is highly negative, while the interactive cost ϕ_{AF} is highly positive. By restricting ϕ_{AF} to zero in this model and in less structural models, Chan (2008) finds that σ_{AF} is highly positive at around 0.9, suggesting that single mothers who have low TANF cost are likely to have low Food Stamp cost as well.

The estimated substitution coefficient ρ has expected magnitude between zero and one.[46] Table 7 computes the work reservation wages for the estimated model assuming there are no transfer programs. As the wage offer increases, the individual moves from no work to part-time then to full-time work. Individuals with low work taste and high non-labor income have lower tendency to work because of higher work reservation wages. At the means, the work reservation wage for

[43] Moffitt (1996) finds that some work programs may increase welfare entry. Blank, Card, and Robins (2000) summarizes a number of studies that find positive effects on welfare participation due to financial incentives programs.

[44] There could be a higher proportion of individuals having negative costs in multiple programs than the proportions having negative costs in separate programs. It could be higher because the estimated interactive participation cost is positive, but the estimated correlation between TANF and Food Stamp cost errors is negative and offsets the effect.

[45] See the literature review for details about welfare dependence.

[46] The elasticity of substitution is 1/(1-0.65)=2.86. The standard error is tiny at 0.0002. This is a common potential problem in the estimation of utility parameters especially the substitution coefficient. A variety of dynamic, pooled and static models estimated in Chan (2008) give the range of estimated ρ between 0.6 and 0.7. Static models give larger standard errors at around 0.01.

Table 8: Wage and Income Elasticities by Wage and Taste for Work

Wage	E_w^u	E_N	H^*	E_w^u	E_N	H^*	E_w^u	E_N	H^*
	Low Work Taste			Mean Work Taste			High Work Taste		
\$6.0	n/a	n/a	0.0	2.88	-0.11	34.6	0.54	-0.01	139.9
\$8.0	9.18	-3.31	1.5	1.36	-0.05	54.0	0.16	-0.00	154.0
\$12.0	2.63	-0.32	8.5	0.88	-0.01	94.0	0.08	-0.00	161.4

Note: Substitution coefficient $\rho = 0.65$ and non-labor income $N = 120$. E_w^u, E_N, H^* denote the uncompensated wage elasticity, income elasticity, and the optimal continuous work hours respectively. Results are shown with cases -1,0,+1 standard deviations away from the mean work taste ϕ_H. The budget constraint is assumed without transfer programs.

full-time work is \$5.18 per hour. Its log value is 1.64, which is about one standard deviation less than the mean log wage. This implies that if there were no transfer programs, the individual at the mean would have had around 84% chance of working full-time.

Table 8 reports the estimated elasticities.[47] At the means of the log wage and the work taste, where the compensated and uncompensated wage elasticities are 1.49 and 1.33 respectively and the income elasticity is -0.04. The absolute values of the elasticities decrease in wage. Individuals with high work taste have inelastic labor supply. Those with low work taste have highly elastic labor supply, but it is highly unlikely that they work at all. The income elasticity is in general very low. Both the wage and income elasticities do not vary much by non-labor income.

Table 9 reports the simulated distribution of choices from the model.[48] Part-time work is over-predicted among program non-participants. There is also a tendency to over-predict program participation among full-time workers. Table 10 reports the average program benefit[49] and equivalent variation (EV) from TANF, Food Stamp, EITC and Federal taxes combined.[50] The table also presents results from three other models estimated in Chan (2008). The pooled models have a time limit dummy variable in the TANF cost equation which has value 1 if the eligibility horizon of the individual is longer than the time limit length. In all models, the EV is higher than the

[47] The CES utility term restricts the sign of the elasticities.

[48] A Pearson chi-square goodness-of-fit test is performed on the log wage distribution as in Keane, Moffitt, and Runkle (1988) using the static model, which has 2433 non-missing wages. Log wages are divided by 78 equal spaced intervals from 0 to 4 (80 in total), and the empirical frequencies are compared with the predicted distribution of log wages derived from simulation. The chi-square statistic is 501.95, and is rejected at the 1% level either with 80 or 80-45=35 (number of estimated parameters in the model is 45) degrees of freedom, hence rejecting normality of errors. The relative spike of the actual distribution of log wage near 1.60 (or wage \$4.95) and sharp drop below is the main part not consistent with the predicted distribution. The federal minimum wage in early 1996 was 4.25 and 5.15 in late 1999, so the minimum wage may have contributed directly to the rejection of the null hypothesis.

[49] The average TANF, Food Stamp, EITC and Federal Taxes benefits are \$47,\$68,\$97,-\$162 respectively.

[50] A detailed analysis of the EV is provided in the appendix.

Table 9: Simulated Distribution of Choices

Program Participation	Labor Supply			
	No Work	Part-Time	Full-Time	Column Total
No TANF, No Food Stamp	8.7	18.2	41.2	68.1
With TANF, No Food Stamp	0.8	0.5	1.5	2.8
No TANF, With Food Stamp	6.6	3.6	5.3	15.6
With TANF, With Food Stamp	8.5	2.2	2.8	13.5
Row Total	24.6	24.6	50.8	100.0

Note: Part-time and full-time work are 20 and 40 weekly hours in the model respectively. Simulations size: 36 per person per period for transitory components, 5 per person for the permanent component.

program benefit, suggesting the presence of negative participation costs among some individuals. As expected, when the TANF and Food Stamp costs are restricted to zero, the program benefit and the EV increase substantially as more people are drawn into TANF and Food Stamp. The deadweight loss due to labor supply distortions is approximately 25 percent.[51]

Table 11 reports the mean marginal effects of selected socioeconomic and program variables on major outcomes. Residence in the south, higher education and age, being white, and having less and older children increase work and reduce program participation. Exogenous increase in wage increases labor supply and reduces program participation, and in particular it reduces Food Stamp participation much more than TANF, suggesting that Food Stamp caseloads are more sensitive to financial status. Reduction in unemployment increases work but it does not affect program participation much.[52] TANF sanctions reduces TANF participation by around 2% and has large effects on other outcomes as well. The effects of expanded disregards are very small.

A number of interesting policy implications can be drawn from the marginal effects. For example, the marginal EV-benefit ratio of increasing the EITC bracket and the phase-in rate are around 1 as opposed to 0.47 for Food Stamp benefit and 0.56 for TANF benefit This suggests that on average, it is more 'efficient' to expand EITC instead of TANF or Food Stamp.[53]

[51] Under the presence of participation costs, the share of the deadweight loss could be lower than 25% because less people are on TANF and/or Food Stamp, which are the programs that generate most labor supply distortions. The EV is considerably higher in the pooled random effect model. The estimated standard deviations of the transitory and permanent components of TANF costs are 134 and 103 respectively, which are higher than in the dynamic model with random effects. The high variance of unobserved errors could be picking up variations in the option value.

[52] Since the unemployment rates used are concurrent and their variations comes mainly from across states, it is suspected that the inclusion of lagged unemployment rates may change the results. Lagged unemployment rates have been used in state level studies such as Wallace and Blank (1999) and Ziliak, Figlio, Davis, and Connolly (2000) and are found to be a better predictor of AFDC caseload than concurrent unemployment rates.

[53] The EITC generates 'desirable; effects on work incentives and earnings as well. But of course, this reduces to the longstanding debate about whether a negative income tax system should replace traditional transfer programs.

Table 10: Simulated Program Benefit and Equivalent Variation in Different Models

		Other Models		
	Dynamic(RE)	Dynamic	Pooled	Pooled(RE)
Program benefit, with participation costs	\$49.8	\$46.7	\$54.6	\$46.2
EV, with participation costs	\$70.7	\$86.9	\$112.0	\$158.0
Program benefit, no participation costs	\$259.7	\$264.0	\$267.1	\$262.1
EV, no participation costs	\$193.7	\$199.6	\$204.6	\$198.4

Note: 'RE' denotes random effects. The 'no participation costs' cases restrict TANF and Food Stamp costs as zero. Simulation size for non-random-effects models: 180 per person per period. For random-effects models: 36 per person per period for transitory components, and 5 per person for the permanent component.

Table 11: Mean Marginal Effects of Selected Variables

	P_H	$\bar{H}$	P_A	P_F	Weekly Earnings	Monthly Benefit	Monthly EV
Individual Characteristics:							
South dummy	1.63	0.72	-5.02	-0.75	-14.20	10.86	-41.77
Years of education	3.86	1.68	-1.15	-3.42	47.93	-59.24	-60.78
Age	0.53	0.21	-0.50	-0.65	6.11	-8.54	-10.98
White dummy	4.23	1.41	-8.80	-13.16	28.07	-66.89	-129.70
No. children less than 18	-1.85	-0.81	1.74	1.37	-7.17	10.10	28.09
Avg age of children less than 18	0.95	0.44	-0.31	-0.48	3.94	-3.91	-8.68
State Characteristics:							
Unemployment rate	-1.70	-0.82	0.01	-0.03	-7.48	4.68	9.72
Sanction dummy	1.16	0.36	-4.17	-2.99	2.83	-14.57	-47.44
Non-lifetime limit adjustment	-0.83	-0.26	2.99	2.14	-2.05	10.38	34.26
Error Equations:							
Log wage	19.89	7.88	-8.57	-26.05	400.86	-524.57	-475.36
Work taste(ϕ_H)	23.61	11.73	-0.07	0.92	105.36	-67.89	-130.48
TANF cost(ϕ_A)	-0.05	-0.02	0.19	0.13	-0.12	0.64	2.20
Food Stamp cost(ϕ_F)	-0.13	-0.04	0.13	0.76	-0.34	1.71	3.24
Budget Constraint Variables:							
TANF dollar disregards*	0.34	0.00	0.14	0.04	-0.01	1.21	0.90
TANF percent disregards	0.02	0.00	0.02	0.00	0.01	0.09	0.08
TANF Benefit*	-0.77	-0.31	1.46	0.82	-2.19	15.96	8.87
Food Stamp benefit*	-2.15	-0.86	1.55	9.49	-6.25	54.53	25.60
EITC lowest bracket**	0.34	0.18	-0.12	-0.16	0.84	13.50	13.25
EITC phase-in rate	0.19	0.03	-0.05	-0.11	0.12	3.26	3.31
EITC phase-out rate	0.00	-0.04	0.00	0.01	-0.33	-1.03	-1.55
First federal tax rate	-0.01	-0.05	0.00	0.01	-0.65	-3.32	-4.29
Payroll tax rate	-0.23	-0.13	0.07	0.15	-1.22	-9.53	-11.12

*Note: $P_H, \bar{H}, P_A, P_F$ denote percentage who work, mean weekly work hours, TANF participation and Food Stamp participation respectively. The values reported are responses to one unit of change of the variables. The increment for computing the marginal effect is 10% of the mean value of the variable. The mean marginal effects are the average of the marginal effects of all individuals. Number of simulations: 100 per person per period for transitory errors, 20 per person for the permanent component. *Values multiplied by 100. **Values multiplied by 1000.*

Table 12: Simulated Outcomes by Time Limit Types, 1996-1999

Type(in months)	P_H	$\overline{H}$	P_A	P_F	Earnings	Benefit	EV	Income
No Limit	74.0	24.8	21.4	32.6	275.7	66.2	85.9	1169
Periodic 24 of 60	74.9	25.3	18.1	31.0	277.4	50.3	-	1160
Actual Limits (baseline)	75.4	25.2	16.3	29.1	279.2	49.8	70.7	1167
Benefit-Waiting 24 then 24	75.6	25.3	15.7	28.7	279.9	45.7	-	1165
Lifetime 43	75.9	25.4	14.6	27.9	280.8	41.8	61.4	1165

Note: $P_H, \bar{H}, P_A, P_F$ are: employment, mean weekly work hours, TANF participation, Food Stamp participation. Non-lifetime limits are simulated by separate structural dynamic models. The EV's of non-lifetime limits are not calculated. Number of simulations: 36 per person per period for transitory components, 5 per person for the permanent component.

6.2 Effects of Time Limits within the Sample Period (1996-1999)

6.2.1 Effects of Time Limits by Type and Length

The panel is relatively short at 28 months on average, but it follows individuals immediately after the welfare reform and hence contains valuable information about its early impacts. Both the data and simulations show that very few individuals (around 0.5%) hit the limits before the sample period ends.[54] Table 12 shows the counterfactual outcomes under different types of time limits. The non-lifetime limits are simulated by separate structural models. They have much smaller effects than lifetime limits of equal length but do not differ fundamentally from lifetime limits. TANF participation decreases more in proportion than the increase in employment and earnings. Food Stamp participation decreases as individuals tend to participate in both TANF and Food Stamp together. Benefit reduces as well, but total income does not change much.[55]

Table 13 presents the counterfactual outcomes under different lifetime limit lengths. There are slight self-selectivity patterns when the time limit is made more stringent. The per-recipient Food Stamp benefit increases, suggesting that individuals who receive more Food Stamp benefit tend to remain in the program. In contrast, the per-recipient TANF benefit increases slightly then drops abruptly. There are two forces working in opposite directions. As in Food Stamp, individuals who receive low TANF benefit tend to leave the program. However, those who receive high TANF benefit also tend to leave, especially when the time limit is stringent. This could be because they know that the loss of TANF benefit due to upon hitting the limits are high, causing them to leave

[54] As the sample period is short, these results are best presented as mean impacts without considering any dynamics.

[55] This conclusion does not consider the effects on medicaid or other programs and assumes that exogenous non-labor income do not change due to time limits.

Table 13: Simulated Outcomes by Time Limit Lengths, 1996-1999

	No Limit	L96	L72	L48	L24	L12
TANF benefit per recipient/100	2.70	2.74	2.75	2.74	2.68	2.57
Food Stamp benefit per recipient/100	2.26	2.30	2.32	2.38	2.45	2.54
Weekly earnings per worker/100	3.73	3.72	3.72	3.71	3.68	3.66
EITC per worker/100	1.29	1.29	1.29	1.29	1.30	1.32
Fraction of workers who are part-time	0.32	0.33	0.32	0.33	0.33	0.33
Monthly income	1169	1169	1168	1166	1161	1156
$\Delta EV/\Delta B$ relative to no time limit	-	0.80	0.88	0.98	1.16	1.34

Note: The numbers following L denote the time limit length in months. $\Delta EV/\Delta B$ is the ratio of the reduction of EV to that of program benefit using 'No Limit' as the baseline case. Number of simulations: 36 per person per period for transitory components, 5 per person for the permanent component.

early.[56] Earnings per worker decreases and EITC per worker increases, suggesting that new workers on the margin earn less on average. The percentage of workers who are part-time remains constant, suggesting that new workers on the margin earn less not because of lower intensity of work but because of lower wage. Income only reduces very slightly.

The last row presents the ratio of the reduction of the EV to the reduction of the program benefit due to a time limit. A larger ratio reflects a larger loss in the nonmonetary well-being, and it equals one if the loss is zero. Theoretically, imposing a time limit has two offsetting effects on the nonmonetary well-being. The deadweight loss reduces because of fewer participants, but the direct utility loss may increase or decrease depending on who stays on the programs. The ratio is larger than one in time limits under 24 months, but it is close to one in actual time limits.[57] Under long time limits, the ratio is less than one, implying a net gain in the nonmonetary well-being.

6.2.2 The Role of Time Limits in the Early Post-Reform Era

Table 14 compares the relative importance of time limits to other socioeconomic and policy changes that occurred from March 1996 just before the reform to around mid 1998.[58] Results from dynamic and the pooled models[59] are shown so that the fully structural and the less structural models can be compared. The predicted total change is the predicted outcomes of the dynamic or pooled model estimated with panel data 1996-1999, minus the predicted outcomes of the static model estimated

[56] There are also more forced exits due to hitting among those who receive high TANF benefit.
[57] The effects of actual time limits are closest to that of a lifetime limit of 48 months in the table.
[58] The panel of post-reform data is unbalanced and has most observations in mid-1998.
[59] Please see discussions on Table 10 for the details of construction of the pooled model.

Table 14: Relative Importance of Components, 1996-1999

	Dynamic, Random Effect				Pooled, Random Effect			
	P_H	$\overline{H}$	P_A	P_F	P_H	$\overline{H}$	P_A	P_F
Predicted total change, 1996-1999	8.9	3.0	-9.8	-6.1	8.3	3.0	-9.6	-6.4
Percentage of change unexplained by model	37.2	27.8	17.0	-2.9	37.1	28.9	31.7	18.1
Composition of Change Explained by Model(%):								
TANF Time Limits	25.1	18.6	62.7	56.2	20.7	16.2	63.1	58.2
TANF Sanctions	10.4	8.4	25.6	24.0	5.6	4.5	16.8	15.2
TANF disregards	2.9	0.0	-1.8	-0.0	3.0	0.0	-1.2	-0.0
Unemployment rate	38.1	47.6	0.2	-0.6	44.5	52.3	0.4	-1.4
Other exclusion restrictions	3.9	3.6	3.3	5.7	4.8	4.1	6.8	8.8
Demographics	19.6	21.8	10.0	14.8	21.5	22.9	14.1	19.3

Note: Other exclusion restrictions: metro residence, share of employment in manufacturing, and AFDC administrative expense. Demographics are age and average age of children in the sample which increased by two years on average. Number of simulations: 36 per person per period for transitory components, 5 per person for the permanent component.

with cross-section data from March 1996. It is then partitioned into explained changes due to various policy and socioeconomic components and unexplained change by the models.[60]

The compositions of explained changes are similar in both models. Time limits contribute around half of the explained changes in TANF and Food Stamp participation, followed by sanctions at around 20%. The share of time limits is larger than found in most existing studies.[61] Unemployment rates contribute around 40% of the explained increase in employment, followed by time limits at around 20%. Expanded TANF disregards has little effects. The dynamic model explains program participation better than the pooled model probably because it explicitly models option values. The dynamic model does not predict employment changes better. Both models fail to explain around 30% of changes in employment. This could be due to work requirements, a major component of welfare reform not included in the analysis which is expected to have higher effects on work than on program participation.

[60]To derive the explained change of a specific component, pre-reform data in March 1996 for that component is used to replace the corresponding part in the panel data. Outcomes are predicted from the dynamic or pooled model using the modified panel data, then pre-reform predicted outcomes are used to subtract from them. Except for TANF time limits, the explained changes of components are computed from the marginal effects table. Results are similar when explained changes are computed directly. Since panel data is used, demographic characteristics especially age and average age of children are controlled.

[61]Existing studies may underestimate the effects of time limits. The econometric implications of not omitting option values are explained in the the model section. Time limits and sanctions may also pick up effects of other components of welfare reform not controlled for in the models, and they may pick up the effects of declining unemployment which fail to explain the decrease in program participation in both models. Wallace and Blank (1999) finds that the decline of the unemployment rate explained 19% of the decline in AFDC/TANF caseloads and 38% of the decline in Food Stamp caseloads from 1994 through mid 1998. But as they note, the decline of the unemployment rate mainly occurred before 1996. Overall, large amounts of unexplained changes in previous studies such as Wallace and Blank (1999) are mostly attributed to TANF.

Table 15: Dynamic Effects of Time Limit on Average Population, Simulation of 10 Years

	No Limit	Lifetime Limit 43 Months			
	Average	First period	Last period	Change(%)	Average
Percentage who work	72.1	73.4	76.1	4	74.7
Average weekly work hours	23.8	24.3	25.2	4	24.7
TANF participation rate	23.2	17.6	8.5	-52	13.5
Food Stamp participation rate	34.1	30.0	23.4	-22	27.3
Weekly earnings	258.6	261.2	268.7	3	265.7
Program benefit	90.0	71.8	31.9	-56	53.3
Equivalent variation	111.5	95.4	6.0	-94	56.5
Monthly income	1122	1116	1106	-1	1116
Option value as percentage of mean ϕ_A	-	7.36	10	35	9.39

Note: Percent change is computed between the first and last periods. Option value as percentage of mean ϕ_A is the option value of time limits $\mathcal{O}$ as a percentage of mean predicted TANF cost ϕ_A which is -148.29. Number of simulations: 36 per person per period for transitory components, 5 per person for the permanent component.

6.3 Dynamic Effects of Time Limits

To study the the dynamic effects of time limits, a universal lifetime limit of 43 months is applied to the sample, who are assumed to have the same eligibility horizon of 10 years. [62] Their behavior are then simulated for 10 years assuming no changes in other characteristics.

6.3.1 Average Population

Table 15 reports the average dynamic response of the population to the time limit. The first period reports the immediate response to the time limit. TANF participation drops immediately by 24% (or 5.6 percentage points). The outcomes continue to deepen over time. TANF and Food Stamp participation drop from the first to the last period by 52% and 22% cumulatively. Employment increases slightly by 2.6 percentage points and weekly earnings by $7. Income changes very little. The EV drops immediately by 15% and by roughly the same magnitude ($16) as the drop in the program benefit. However, the EV drops much more sharply over time by a further $89 (or 94%), as opposed to the program benefit which drops by $40. This implies that there is significant loss in the nonmonetary well-being over time. By the last period, many individuals who have negative TANF costs may have hit the limit and therefore suffer from direct utility losses.

Around 10% of individuals eventually hit the limit. If there were no forward-looking behavior,

[62] The average time limit length for those of are subject to time limits is 43 months, and the eligibility horizon is derived from the sample average of the average age of children.

Table 16: Characteristics of Time-Limit Leavers, Simulation of 10 Years

	All individuals	Time-limit leavers
Mean Observable Characteristics:		
South dummy	0.39	0.30
Years of education	12.15	11.47
Age	33.43	36.93
White dummy	0.71	0.58
Number of Children less than 18	1.76	2.34
Mean Unobservable Characteristics:		
Predicted log wage ($X_w\beta_w$)	2.11	2.09
Predicted Work taste ($X_H\beta_H$)	-1.59	-1.66
Predicted TANF cost ($X_A\beta_A$)	-148	-140
Predicted Food Stamp cost ($X_F\beta_F$)	-61	-59
Wage error (ϵ_{wt})	-	0.00
Work taste error (ϵ_{Ht})	-	0.00
TANF cost transitory error (ϵ_{At})	-	0.50
Food Stamp error (ϵ_{Ft})	-	-0.16
TANF cost permanent component (μ_A)	-	97

Note: Number of simulations: 36 per person per period for transitory components, 5 per person for the permanent component.

26% of individuals would have hit. In addition, if there were no individual heterogeneity, only 0.05% of them would have hit,[63] indicating that individual heterogeneity causes hitting. The average option value is close to 10% of the mean predicted TANF cost. Marginal effects[64] show that the option value reduces TANF participation by roughly 3.8% if it were a constant.

6.3.2 Time-Limit Leavers

Time-limit leavers are individuals who eventually hit the time limit.[65] Table 16 compares them with the average population. Time-limit leavers differ from the average population mainly in the unobserved individual heterogeneity (permanent component) of the TANF cost, which on average is 1.19 standard deviations (or the top 12% in the population) from zero mean. Other unobserved heterogeneities are negligible. Time-limit leavers tend to have lower wage offers, work tastes, TANF costs and Food Stamp costs, but the differences are relatively small.[66] They tend to reside in the

[63] This is computed from the probability of accumulating more than 42 months of TANF in a binomial distribution of 116 months with probability of TANF participation in each period at 0.232. If there were no forward-looking behavior and no heterogeneity, the binomial distribution setting shows that the probability of hitting is 0.00069%.

[64] Marginal effects are computed from the case of no time limits which are not shown in the paper.

[65] There are studies examining issues such as whether they experience material hardship after hitting, why they hit earlier than the others, and how they differ from other types of welfare leavers. See the literature review for more details. The distribution of hitting time has a mean of 86 months with skewness -0.34.

[66] These translate to 0.07, 0.24, 0.23 and 0.4 standard deviations away from the means respectively. Assuming that the predicted values are roughly normally distributed - see basic results section for more discussion - they are at the

Table 17: Dynamic Effects of Time Limit on Time-Limit Leavers, Simulation of 10 Years

	No Limit	Lifetime Limit 43 Months			
	Average	Before Hit	After Hit	Change(%)	Average
Percentage who work	56.7	60.2	75.9	26	65.0
Average weekly work hours	18.4	19.7	24.8	26	21.2
TANF participation rate	69.4	53.9	-	-	37.1
Food Stamp participation rate	73.5	63.4	24.4	-62	51.2
Weekly earnings	204.8	216.2	256.4	19	228.7
Program benefit	342.9	284.3	61.6	-78	217.6
Equivalent variation	554.9	471.5	4.8	-99	322.7
Monthly income	1162	1149	1087	-6	1129
Option value as percentage of mean ϕ_A	-	21.5	-	-	-

Note: Before and After hit are the average outcomes of pre- and post-hit records respectively. Percent change is computed between before and after hitting. Option value as percentage of mean ϕ_A is the option value of time limits $\mathcal{O}$ as a percentage of mean predicted TANF cost ϕ_A which is -148.29. Number of simulations: 36 per person per period for transitory components, 5 per person for the permanent component.

non-south, receive less education, be older, be non-white, and have more children.

Table 17 reports the average dynamic response of time-limit leavers. Under no time limits, they work considerably less (56% versus 72%) and participate considerably more in programs (69% versus 23% in TANF and 74% versus 34% in Food Stamp) than the average population. They also receive four times as much benefits ($343 versus $90) and five times as much EV ($555 versus $112). They have slightly higher monthly income than the average population ($1162 versus $1122) due to higher program benefit.

The table shows that time-limit leavers do not respond much prior to hitting the limit despite higher option values than the average population. Most of the response occurs when they hit. In particular, food Stamp participation drops by 39 percentage points. The average employment level increases by 16 percentage points. The income drops by 6%, and the share of program benefit in income drops from 25% to 6%. The drop in EV is large at $466 and is much sharper than the drop in program benefit,[67] which is mostly due to direct utility losses as many time-limit leavers have negative TANF cost. Their post-hit outcomes are very similar to that of the average population. This is because as time-limit leavers become ineligible for TANF, their main difference from the average population in TANF cost become irrelevant.

53th, 59th, 59th and 66th percentiles of the predicted values respectively.

[67]For the average population, the $\Delta EV/\Delta B$ ratio (as defined in Table 13) is 1.49 on average. For time-limit leavers, the ratio is 1.86 on average.

6.4 Distributional Impacts

6.4.1 Demographic Characteristics

Marginal effects can be used as a means to identify locally the types of individual characteristics that are more affected by time limits. Let $Y_{tl}(z)$ and $Y_{ntl}(z)$ be the mean outcomes of the population with mean characteristics z (e.g. education) under the time limit and without the time limit respectively. Without loss of generality, suppose $Y_{tl}(z) > Y_{ntl}(z)$ (an example is an increase in employment level due to time limits). Consider an incremental increase in the mean characteristics z. The effect of the time limit will be larger for the population with higher mean z if $\frac{\partial(Y_{tl}(z)-Y_{ntl}(z))}{\partial z} \equiv \frac{\partial Y_{tl}(z)}{\partial z} - \frac{\partial Y_{ntl}(z)}{\partial z} > 0$, where the two terms are the marginal effects with and without the time limit respectively. The marginal effects results show that individuals who are younger and non-white, reside in the non-south, have less education, and have more children are more affected by the time limit in all types of outcomes. Intuitively, those who are affected more should tend to have a higher probability to participate in TANF. In general, the typical 'welfare population' is more affected by the time limit.

6.4.2 Time-Limit Leavers

Let the share of effect s_G of an outcome Y on a subgroup G of the population be defined as:

$$s_G \equiv \frac{(\bar{Y}_{tl,G} - \bar{Y}_{ntl,G}) * N_G}{(\bar{Y}_{tl} - \bar{Y}_{ntl}) * N} \tag{21}$$

where $\bar{Y}_{tl}, \bar{Y}_{ntl,G}$ are the mean outcomes of the population and subgroup under the time limit respectively, $\bar{Y}_{ntl}, \bar{Y}_{,ntl,G}$ are the corresponding mean outcomes without the time limit, and N, N_G are the size of the population and the subgroup. The effects of time limits on an average time-limit leaver are much larger than on the average population. Around 30% of the overall change in employment, program participation and program benefit due to the time limit are from time-limit leavers. Around 40% of the overall drop in EV are from time-limit leavers, which is not surprising as they have very low TANF cost.

Many researchers and policy makers are also interested in the size of the 'mechanical effect', defined as the effect of time limits due to post-hit TANF ineligibility of time-limit leavers alone.

Table 18: Characteristics of Subgroups Defined by Predicted Log Wage

		Subgroups by Predicted Log Wage				
	All	1	2	3	4	5
Mean Observable Characteristics:						
South dummy	0.39	0.61	0.43	0.36	0.27	0.27
Years of education	12.2	9.6	11.8	12.2	12.4	14.8
Age	33.4	26.8	28.4	32.3	37.8	41.8
White dummy	0.71	0.63	0.59	0.72	0.77	0.83
Number of Children less than 18	1.76	1.86	1.80	1.81	1.73	1.57
Mean Unobservable Characteristics:						
Predicted log wage ($X_w\beta_w$)	2.11	1.70	1.98	2.10	2.23	2.54
Predicted Work taste ($X_H\beta_H$)	-1.59	-1.80	-1.64	-1.60	-1.55	-1.36
Predicted TANF cost ($X_A\beta_A$)	-148	-134	-133	-145	-157	-171
Predicted Food Stamp cost ($X_F\beta_F$)	-61	-58	-60	-61	-62	-64

Note: Subgroups are ordered by ascending log wage. Number of individuals=3087.

There are 2.6% of post-hit records. The mechanical effect constitutes around 20% of the total effect of time limits. In particular, in the last period alone, the mechanical effect is as large as 50%, which is a significant amount as only 10% of the population have hit in the last period.

6.4.3 Income, Wage and TANF Cost Subgroups

A number of studies in the welfare reform literature look at the distributional impacts of policies using endogenous economic characteristics, especially income.[68] Here, the population is first divided into five equal 20-percentile subgroups ranked by predicted income under no time limits.[69] The average income in the subgroups are $707, $941, $1075, $1219 and $1680. The income subgroups possess very similar characteristics as wage subgroups, which is discussed below.[70] Then, the time limit is imposed on each of the subgroup and their average income are simulated over time. For all subgroups, the income levels drop very slightly on average and over time by less than $20. None of the subgroups are more affected by the time limit then the others.

The population is then divided into 5 equal subgroups ranked by the predicted log wage.[71] Table 18 shows the characteristics of the wage subgroups. On average, low wage subgroups have

[68]Schoeni and Blank (2000), Bitler, Gelbach, and Hoynes (2006) and Meyer and Sullivan (2008) study subgroups in different income percentiles. Bitler, Gelbach, and Hoynes (2006) point out that the subgroups should not base on exogenous socioeconomic characteristics such as education but should instead base on endogenous economic outcomes.

[69]This is done by simulating the behavior of individuals under the case of no time limits.

[70]In particular, the predicted wage in each income subgroup is very close to the predicted wage in each wage subgroup. It can almost be concluded that the wage offer is the primary factor in determining the income level.

[71]Predicted levels are used instead of actual levels to exclude possible self-selectivity.

Table 19: Share of Effects of Time Limit on Subgroups, Simulation of 10 Years

	Share of Effect (%)			
	P_H	P_A	B	EV
Twenty-Percentile Subgroups Divided By:				
Predicted Log Wage				
Lowest	30	31	30	30
Low-medium	29	28	29	27
Medium	23	22	23	25
Medium-High	13	12	13	11
Highest	5	7	5	7
TANF Cost Error, Permanent Component (μ_A)				
Lowest	0	0	0	0
Low-Medium	1	1	2	0
Medium	8	7	9	2
Medium-High	25	23	26	12
Highest	65	70	63	86

Note: P_H, P_A, B denote percentage who work, TANF participation, program benefit. Number of individuals=3087. Number of simulations: 36 per person per period for transitory components, 5 per person for the permanent component.

lower work taste and TANF cost than the rest of the population. Low wage individuals tend to be younger and non-white, reside in the south, receive less education, and have more children. Table 19 computes the share of the effects of the time limit on subgroups of the population. The time limit disfavors low wage subgroups slightly. For example, individuals at the lowest 20 percentiles of predicted log wage bear about 30% of the overall reduction in program benefit due to the time limit. This is not surprising because the financial and non-financial characteristics of low wage subgroups make them more likely to participate in TANF.

To look at welfare dependence, the population is divided into 5 equal subgroups ranked by the realization of the unobserved individual heterogeneity (permanent component) of the TANF cost, which is the major source of heterogeneity of TANF cost. Table 19 shows that individuals who have the highest 40 percentiles of welfare dependence[72] bear about 90% of the total effects of time limits. For example, out of all reductions in the program benefit, 90% of them come from these individuals. Impacts are much more unbalanced among TANF cost subgroups than among wage subgroups, implying that time limits put a lot of penalty on individuals who have low TANF costs. In this respect, the time limit policy is very effective in achieving its goal of reducing TANF caseloads within the population with high welfare dependence.

[72] To be precise, this means low unobserved individual heterogeneity in the TANF cost.

7 Conclusions

This paper studies the short and long term impacts of time limits by modeling single mothers' dynamic response and estimating the model using early post-reform data from 1996 to 1999. I show theoretically that time limits exert an effect by increasing the welfare participation cost of single mothers, making them more reluctant to participate than otherwise and resulting in more non-participating eligibles.

After controlling for TANF, Food Stamp, EITC and Federal tax policies and economic conditions especially the unemployment rate, I find that time limits were important in moving single mothers off welfare in the early post-reform era. The declining unemployment rate was important in increasing work. Time limits increased work slightly and did not affect income. Simulation results show that the most significant income drop is roughly 6 percent or 60 dollars per month and occurs when they hit the limits. Unlike the average population, time-limit leavers do not respond much to time limits before they hit. They participate heavily in welfare and do not work, but then shift from welfare to work abruptly when they hit the limits. In particular, the share of program benefit in income drops from 25 percent to 6 percent after they hit the limits.

I use welfare participation cost in the model to formalize the concept of welfare dependence. There are large variations in welfare dependence among single mothers. On average, time-limit leavers have very high welfare dependence. Around 15 percent of the population yield utility from welfare participation even when the benefit is zero. This could be due to peripheral services or subprograms attached to welfare. When they hit time limits, they lose utility previously yielded from these services.

Time limits have disproportionately large effects on single mothers who have high welfare dependence. This may be consistent with the goal of the welfare reform to reduce welfare dependence, but if they have severe barriers to work or other difficulties, changes in policies are recommended to alleviate the impacts. For example, less stringent time limits could be designed for specific targeted subgroups of the population. The time limit in Texas is an existing example. It has time limit lengths that vary by the recipients' levels of education and work experience, which are observable indicators of financial status and welfare dependence.

A Appendix

A.1 Program Benefit Formulas

Let w_i, H_i, N_i be the hourly gross wage, weekly labor supply and monthly exogenous non-labor income respectively.[73] The individual is eligible for TANF if she passes the gross income and net income tests:

$$4w_iH_i + N_i < r_{gi}E_{ni} \qquad \text{and} \qquad \max\{0, (4w_iH_i - D_{Ei})(1 - R_{Ei}) + N_i\} < r_{ni}E_{ni}$$

where E_{ni} is the eligibility standard, r_{gi}, r_{ni} are the gross and net income multiplication factor, and D_{Ei}, R_{Ei} are the eligibility dollar and percent disregards. During the sample period, except in a few states where the benefit percent disregards was 100 percent, the income tests usually did not bind. The benefit formula is

$$B_{Ai} = \max\{0, \min\{M_i, r_i[G_i - \max\{0, (4w_iH_i - D_{Bi})(1 - R_{Bi}) + N_i\}]\}\}$$

where M_i is the benefit maximum of the state, r_i is the ratable, G_i is the benefits standard, and D_{Bi}, R_{Bi} are the dollar and percent disregards. In particular, G_i, M_i and E_{ni} vary by family size.

The Food Stamp program parameters are identical across states. Its benefit level depends on the TANF benefit. For simplicity, it is assumed that the housing deduction is \$250. The gross and net income tests are

$$4w_iH_i + N_i < 1.3 * E_{Fni} \qquad \text{and} \qquad ninc_i < E_{Fni}$$

where the net income and the benefit formula are

$$\begin{aligned} ninc_i &= \max\{0, (0.8)4w_iH_i + N_i + B_{Ai} - 134 - 250\} \\ B_{Fi} &= \max\{0, G_{Fi} - 0.3 * ninc_i\} \end{aligned}$$

E_{Fni} and G_{Fi} are the eligibility and benefit standards respectively and they vary by family size.

The EITC and tax formulas follow the tax tables. During 1996-2000, the phase-in rates for EITC are 34% and 40% and the phase-out rates are 40% and 21.06% for 1 kid and 2+ kids respectively. In 1998, the EITC brackets are {\$6680,\$12260,\$26473} for one kid and {\$9390,\$12260,\$30095} for two kids. For Federal tax, in 1998, the deduction is \$6250, the per person exemption is \$2700, and bracket 1 is \$33950.

A.2 Technical Details of Estimation

A.2.1 Using Approximations of Reservation Values in Estimation by Simulation

Static Model The model has 12 discrete choices with 3 levels of work and 4 program participation combinations. I show that under some regularity conditions,[74] work and program choice reservation values can be constructed and approximated to facilitate estimation by simulation methods. A major observation

[73] Some types of non-labor income are excluded from the formula according to the benefit rules. This distinction is made when benefits are computed.

[74] A more complete theoretical treatment of reservation values of continuous and discrete choice labor supply models with more general utility functions is provided in Chan (2008). For example, under some general conditions, there are $N - 1$ ordered work reservation wages in a labor supply model with N discrete choices.

is that the model can be solved sequentially first for the work choice conditional on program choice, then for the program choice. It can be shown that there are two ordered work reservation work tastes conditional on each program choice. For example, by equating the CES utility term ($(\alpha Y^{\rho} + (1-\alpha)L^{\rho})^{1/\rho}$) for two distinct leisure levels, a work reservation value is

$$\alpha^*_{i,j}(w) \equiv \frac{L_i^{\rho} - L_j^{\rho}}{L_i^{\rho} - L_j^{\rho} + Y_j(w)^{\rho} - Y_i(w)^{\rho}}$$

The individual chooses from no work to part-time then full-time work as α becomes higher.[75] There are 8 work reservation values because the income Y differs by program choice. In estimation, the exact work reservation values are first computed on a grid of w and stored.[76] Then, during the simulation of choice probabilities with random w and α, the approximate work reservation values $\hat{\alpha}^*_{i,j}(w)$ are computed by linear interpolation.[77] The optimal work level conditional on program choice is easily derived by directly comparing α and the approximate work reservation values.

Let $u^*_{kl}(\alpha, w)$ be the optimal CES utility term conditional on TANF choice k and Food Stamp choice l. The model is now reduced to 4 program choices. The optimal program choice can be found by reservation values. Define the program choice reservation values relative to choice $\{P_A = 0, P_F = 0\}$ as

$$\begin{aligned}
\phi_1^*(\alpha, w) &\equiv u^*_{10}(\alpha, w) - u^*_{00}(\alpha, w) \\
\phi_2^*(\alpha, w) &\equiv u^*_{01}(\alpha, w) - u^*_{00}(\alpha, w) \\
\phi_3^*(\alpha, w) &\equiv u^*_{11}(\alpha, w) - u^*_{00}(\alpha, w) - \phi_{AF}
\end{aligned}$$

The exact program choice reservation values are first computed on a 2-dimensional grid of w and α and stored.[78] Then, during the simulation of choice probabilities with random w, α, ϕ_a and ϕ_f, the approximate program choice reservation values $\hat{\phi}_1^*(\alpha, w), \hat{\phi}_2^*(\alpha, w), \hat{\phi}_3^*(\alpha, w)$ are computed by linear interpolation, and the optimal program choice is found by locating the highest of the values $\{0, \phi_A - \hat{\phi}_1^*, \phi_F - \hat{\phi}_2^*, \phi_A + \phi_F - \hat{\phi}_3^*\}$, which are the relative optimal utilities to choice $\{P_A = 0, P_F = 0\}$.

Dynamic Model Reservation values computed from the static model can be used directly in the dynamic model. In each period, the conditional work choice is computed in the same way as in the static model. The optimal program choice is found by finding the highest of values

$$\Delta u^*(\mathcal{O}(t, S, T); \vec{\epsilon}) \equiv \max\{0, \phi_A - \hat{\phi}_1^* - \mathcal{O}(t, S, T), \phi_F - \hat{\phi}_2^*, \phi_A + \phi_F - \hat{\phi}_3^* - \mathcal{O}(t, S, T)\} \tag{22}$$

where $\mathcal{O}(t, S, T)$ is the option value of time limits computed from backwards recursion.

[75] Suppose the conditional work reservation values are α_1^* and α_2^*, where $\alpha_1^* > \alpha_2^*$. The conditional optimal work choice is: $H^* = 40$ if $\alpha > \alpha_1^*$; $H^* = 20$ if $\alpha_1^* \geq \alpha > \alpha_2^*$; $H^* = 0$ if $\alpha \leq \alpha_1^*$.

[76] 7 gridpoints are usually adequate but in practice 15 gridpoints are used.

[77] The same procedure is repeated by individuals. The reason to compute the reservation values for each individual is that they depend on exogenous non-labor income which enters structurally in Y.

[78] For workers, a grid of w is not necessary. In practice, 7 gridpoints on α and 15 gridpoints on w are used.

A.2.2 Getting around Multi-Dimensional Integration in the Expected Value Function

The main computational difficulty in obtaining the option value is that the expected value function $E_t V_{t+1}(S, \vec{\epsilon}_{t+1})$ consists of a four-dimensional integral with the random variables $w, \alpha, \phi_A, \phi_F$ correlated with one another. I show that using reservation values, it is possible to largely get around the integral without having to use Monte-Carlo integration methods extensively. First, using a large number of error draws (500 in practice) of w and α, the expected optimal single period utility $Eu^*_{00}(\alpha, w)$ at choice $\{P_A = 0, P_F = 0\}$ is computed. When $S_t = \bar{S}$ (time limit is reached), this is the optimal single period utility, so the expected value is

$$E_t V_{t+1}(\bar{S}, \vec{\epsilon}_{t+1}) = Eu^*_{00}(\alpha, w) + E_{t+1} V_{t+2}(\bar{S}, \vec{\epsilon}_{t+1})$$

Otherwise, it is only part of the expected value. There is an expected relative utility increment captured by (22), which can be numerically approximated as follows. A grid of positive values is set up on the option value.[79] Then for each gridpoint x, the expected relative utility increment is computed by 500 error draws

$$E\Delta u^*(x; \vec{\epsilon}) \approx \frac{1}{500} \sum_{j=1}^{500} \max\{0, \phi_{Aj} - \hat{\phi}^*_{1j}(\alpha_j, w_j) - x, \phi_{Fj} - \hat{\phi}^*_{2j}(\alpha_j, w_j), \phi_{Aj} + \phi_{Fj} - \hat{\phi}^*_{3j}(\alpha_j, w_j) - x\} \quad (23)$$

where the reservation values are approximated by linear interpolation in the static model. Clearly, the expected relative utility increment is decreasing in the option value. The approximate expected value for each t and S can then be computed without integration:

$$E_t V_{t+1}(S, \vec{\epsilon}_{t+1}) \approx Eu^*_{00}(\alpha, w) + E\hat{\Delta} u^*(\mathcal{O}(t, S, T); \vec{\epsilon}) + E_{t+1} V_{t+2}(S, \vec{\epsilon}_{t+1})$$

where $E\hat{\Delta} u^*(\mathcal{O}(t, S, T); \vec{\epsilon})$ is obtained from linear interpolation on the grid of option values. Backward recursion starts from the last period where the option values are set at zero.

A.2.3 Kernel-Smoothed Frequency Simulator based on Reservation Values

In order to use gradient optimization methods in estimation by simulation, kernel-smoothed frequency simulators are often constructed.[80] Here I construct a simulator that is based on reservation values instead of utilities of choices. To construct a simulator for program choice, let an i.i.d. extreme value error term with standard deviation τ_ϕ be added to the terms in (22), so that the program choice k is distributed as multinormial logit[81]:

$$P^\phi(k) = \frac{\exp(\Delta u(k)/\tau_\phi)}{\sum_{k=1}^{4} \exp(\Delta u(k)/\tau_\phi)}$$

where $P^\phi(k)$ is the (smoothed) probability of choosing alternative k in (22) and $\Delta u(k)$ is the kth term in (22). To construct a simulator for work choice, consider two work reservation values $\alpha^*_2(k) > \alpha^*_1(k)$ conditional on program choice k. Add an i.i.d. extreme value error term with standard deviation τ_w[82] to the work taste α,

[79] In practice, 7 gridpoints are used.

[80] For example, McFadden (1989) discusses a variety of such simulators.

[81] Keane and Moffitt (1998) use the same structure in constructing a simulator based on utilities of choices.

[82] In practice, $\tau_\phi = 5$ and $\tau_w = 0.02$ are used after a number of tests.

so that the conditional work choice l is distributed as ordered logit:

$$P^{\alpha}(l|k) = \begin{cases} \frac{1}{1+\exp(-(\alpha_1^*(k)-\alpha)/\tau_w)} & \text{when} \quad l = 0 \\ \frac{1}{1+\exp(-(\alpha_2^*(k)-\alpha)/\tau_w)} - \frac{1}{1+\exp(-(\alpha_1^*(k)-\alpha)/\tau_w)} & \text{when} \quad l = 20 \\ 1 - \frac{1}{1+\exp(-(\alpha_2^*(k)-\alpha)/\tau_w)} & \text{when} \quad l = 40 \end{cases}$$

The smoothed frequency simulator for individual i given parameters $\vec{\theta}$ and exogenous characteristics $\vec{X}_i$ is

$$P^S(l_i^*, k_i^*|\vec{X}_i, \vec{\theta}) = \frac{1}{N_s}\sum_{j=1}^{N_s} P_j^{\phi}(k_i^*) P_j^{\alpha}(l_i^*|k_i^*)$$

where N_s is the simulation size, and k_i^*, l_i^* are the observed program and work choices for the individual.

A.2.4 Likelihood Function

For each individual, from the first period to last period G_i, S_{it} (accumulated months on TANF) can be calculated using observed TANF participation in each period.[83] Let $\vec{\theta}$ be the vector of parameters to be estimated and $\vec{X}_{it}$ be the observed socioeconomic characteristics. The individual knows the realization of the unobservable permanent effect μ_{Ai} of the TANF cost which remains constant in all time periods. Let its normal probability distribution be $f(\mu_{Ai})$. Let $P(y_{it}|\vec{X}_{it}, \vec{\theta}, w_{it}, S_{it}, \mu_{Ai}, t)$ be the conditional probability of choosing choice y_{it} when the wage can be observed, and let $P(y_{it}|\vec{X}_{it}, \vec{\theta}, S_{it}, \mu_{Ai}, t)$ be the corresponding conditional probability when the wage cannot be observed. These probabilities are obtained from the kernel-smoothed frequency simulator. The log likelihood is

$$\sum_{i=1}^{N} \ln \int_{-\infty}^{\infty} \prod_{t=1}^{G_i} \left(P(y_{it}|\vec{X}_{it}, \vec{\theta}, w_{it}, S_{it}, \mu_{Ai}, t) g(w_{it}|\vec{X}_{it}, \vec{\theta}) \right)^{\mathbf{1}(H_{it}>0)} P(y_{it}|\vec{X}_{it}, \vec{\theta}, S_{it}, \mu_{Ai}, t)^{\mathbf{1}(H_{it}=0)} f(\mu_{Ai}) d\mu_{Ai}$$

where $g(w_{it}|\vec{X}_{it}, \vec{\theta})$ is the conditional normal pdf of the wage and H_{it} is the observed labor supply. The quadrature method replaces the integral with a weighted sum based on three points of μ_{Ai}.

A.3 Equivalent Variation of a Transfer Program with Participation Cost

The Hicks' equivalent variation of a transfer program is the monetary lump-sum equivalent of the utility gain of participating in the program. I show that under general conditions, it can be broken down into three parts - 1) the received monetary program benefit, 2) the deadweight loss due to labor supply distortions, and 3) the direct utility loss/gain due to the positive/negative program participation cost.[84]

Suppose an individual has a utility function $u(L, Y) + \phi P$, where L, Y, P are leisure, income and program participation respectively, ϕ is the program participation cost, and $u(.)$ is strictly increasing and quasiconcave. Consider a classic optimization problem of labor supply and program participation. Let the gross wage be w

[83] This is true when the time series is all composed of actual observations. Cases with imputed records are discussed in Chan (2008). It can be easily be shown that the estimator is still consistent if the likelihood function is conditioned upon simulated values of S_{it}, given that the simulation size is large.

[84] The equivalent instead of compensating variation is used because of a nonlinear budget constraint. For welfare evaluation studies with nonlinear budget constraints, see Creedy and Kalb (2005) and Reiss and White (2006).

and exogenous non-labor income be N. Let the program benefit function be $\mathbb{B}(w, L, N)$, which can consist of multiple segments, notches and kinks. Then, construct a duality problem with V and e being the indirect utility and minimum expenditure functions from the linear budget constraint with wage w conditional on $P = 0$. Suppose it is optimal for the individual to participate in the program, where she receives benefit B at the optimal choice $\mathbf{x}^*$. For simplicity, suppose her utility is maximized at a smooth segment (not at any kink) of the budget constraint. Let the local net wage rate around $\mathbf{x}^*$ be w'. The equivalent variation is

$$e(w, V(w', N + B + b) + \phi) - e(w, V(w, N)) \equiv e(w, V(w', N + B + b) + \phi) - N \geq 0$$

where b is an adjustment such that the optimal choice $\mathbf{x}^*$ lies exactly on the linear budget constraint represented by the parameters $(w', N + B + b)$. By construction, this is the linear extension of the segment of the budget constraint where the individual's utility is maximized. The received monetary program benefit and the monetary equivalent of the deadweight loss are

$$B \equiv e(w, V(w, N + B)) - e(w, V(w, N)) > 0$$
$$e(w, V(w', N + B + b)) - e(w, V(w, N + B)) \leq 0$$

Clearly, as B is the actual amount of benefit received, $\mathbf{x}^*$ is a feasible point in the optimization problem with the linear budget constraint with parameters $(w, N + B)$. Therefore, $V(w, N + B) \geq V(w', N + B + b)$ and the deadweight loss is non-positive. In particular, if $w \neq w'$, the deadweight loss is strictly negative and if $w = w'$, the deadweight loss is zero.[85] The monetary equivalent of the direct utility loss is

$$e(w, V(w', N + B + b) + \phi) - e(w, V(w', N + B + b)) \lesseqgtr 0$$

Its sign depend on the sign of ϕ. The deadweight loss and the direct utility loss together form the loss of the 'nonmonetary well-being' of the individual who participates in a transfer program.

A.4 List of Terms used in the Literature

- Anticipatory effect: The change of behavior prior to hitting the time limit.
- Eligibility horizon: Under AFDC/TANF, single mothers can apply for benefits until the child reaches 18 years of age. This is the remaining number of months until the child turns 18.
- Earnings disregards: Percent disregards refer to the rate of benefit reduction of a program when earnings increase. Dollar disregards refer to the amount of earnings not counted in the computation of benefits.
- Hitting/reaching the time limit: Having accumulated months of benefits equal to the time limit length.
- TANF/Food Stamp cost: Direct utility loss due to participation of programs. May include stigma, hassle, and nonmonetary benefits not captured by the program benefit formula such as peripheral services valued by individuals.
- Time limit length: The maximum number of months of benefits allowed under a time limit.
- Time-limit leavers: Individuals who at some point in time are forced to quit TANF due to time limits.
- Welfare dependence: Generally refers to the 'natural' tendency to participate in welfare determined by observable or unobservable characteristics.

[85] In a discrete choice model, the deadweight loss can only be negative when the labor supply is different under a transfer program.

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