
A Stock-Flow Analysis of the Welfare Caseload

Jacob Alex Klerman
Steven J. Haider

ABSTRACT

This paper reconsiders the methods used in previous studies to assess the welfare caseload movements during the 1990s. We develop a model in which the welfare caseload is the net outcome of past flows onto and off of the caseload and show that such a stock-flow model can explain some of the anomalous findings in previous studies. We then estimate the stock-flow model using California administrative data. We find that approximately 50 percent of the caseload decline in California can be attributed to the declining unemployment rate. These estimates are more robust and larger than those obtained when applying more typical methods to the same California data.

Jacob Alex Klerman is a senior economist at RAND and a professor of economics at the Pardee RAND Graduate School. Steven J. Haider is an assistant professor of economics at Michigan State University. This work was funded in part by U.S. Department of Health and Human Services, Office of the Assistant Secretary for Planning and Evaluation (#99ASPE34A and #00ASPE353A) and by NICHD grant P50-HD12639. The opinions and conclusions expressed herein are solely those of the authors and should not be construed as representing the opinions or policy of any of the sponsors or related agencies. The data used in this paper come from confidential California administrative data and cannot be provided to others by the authors. Requests for these data should be addressed to the California Department of Social Services. The authors gratefully acknowledge the expert programming assistance of Elizabeth Roth. They also acknowledge the helpful suggestions of two anonymous referees, Jay Bhattacharya, V. Joseph Hotz, Darius Lakdawalla, David Loughran, Kathleen McGarry, Terra McKinnish, Regina Ripahn, Robert Schoeni, and the seminar participants at UC-Berkeley, UCLA, Cornell, IRP 2000 Summer Workshop, Michigan, Michigan State, UNC-Chapel Hill, RAND, Syracuse, and the Upjohn Institute for Employment Research. For information on how to acquire the data, authors may contact either author: Klerman: RAND; 1700 Main Street; Santa Monica, CA 90401; klerman@rand.org. Haider: Department of Economics; Michigan State University; 101 Marshall Hall; East Lansing, MI 48824; haider@msu.edu. [Submitted March 2002; accepted June 2003]

ISSN 022-166XE-ISSN 1548-8004 © 2004 by the Board of Regents of the University of Wisconsin System

I. Introduction

During the 1990s, the welfare caseload peaked and then declined by half.¹ The 1990s also witnessed a robust economic expansion and a series of major welfare reforms. Applying conventional difference-in-difference models to aggregate welfare caseload data, many studies have estimated the relative importance of the economic expansion and welfare reforms in explaining the caseload decline (for example, CEA 1997; Wallace and Blank 1999; and Ziliak et al. 2000; see Blank 2002 for an extensive review). These studies reached widely varying conclusions regarding the cause of the decline. Several studies suggest that these different conclusions are due to differing specifications for the relationship between the current welfare caseload and lags of the explanatory and dependent variables (for example, Figlio and Ziliak 1999; CEA 1999). However, none of the studies explicitly consider the source of these relationships.

This aggregate caseload literature has developed independently of a large literature that examines individual-level flows onto and off of welfare (for example, Hutchens 1981; Blank and Ruggles 1996; and Hoynes 2000). This paper attempts to combine the two literatures by considering the implications of viewing the aggregate caseload, a stock variable, as the net outcome of past flows onto and off of welfare. This stock-flow approach suggests a source for the strong dependence of the caseload on lags of the explanatory variables found in previous studies. Furthermore, it suggests that the conventional models are misspecified and that this misspecification can explain the disparate results across the studies.

Beyond suggesting a critique of the existing literature, the stock-flow perspective also provides for an alternative estimation strategy. Specifically, we estimate the underlying flow relationships from the individual-level data and then simulate the implied impact on the caseload stock. This basic idea has been used to examine many behaviors, including welfare receipt (for example, Boskins and Nold 1975; Hutchens 1981), fertility (for example, Heckman and Walker 1992) and single motherhood (for example, Moffitt and Rendall 1995). Such an approach is not feasible with the available national data, and instead, we use California administrative data. Because these data are only for one state, we are not able to distinguish the impact of policy changes from more general time effects. However, there is sufficient variation to precisely estimate the impact of changing economic conditions.

Our results suggest that approximately half of the caseload decline in California can be attributed to changing economic conditions, as measured by the unemployment rate.² These estimates are substantially larger than the 20–35 percent estimates that are obtained from more typical methods using the same California data. Although the aggregate regressions for California are very similar to their national counterparts, extrapolating from our California stock-flow results to what would be obtained with national data should be done with much caution. The 1990s economic recovery was

1. Here and throughout this paper, welfare refers to the government program that provides cash assistance to the poor, the Aid to Families with Dependent Children (AFDC) program which was replaced by the Temporary Assistance for Needy Families (TANF) program.

2. For a more comprehensive assessment of the caseload decline in California, see the series of reports from RAND's statewide evaluation (for example, Klerman, et al. 2000) and MaCurdy, Mancuso, and O'Brien-Strain (2002).

stronger and welfare reform was implemented later in California as compared with the rest of the nation.

II. Explaining Caseload Changes

Numerous studies have examined the recent declines in the welfare caseload.³ These studies generally specify aggregate regressions in which the log of the caseload per capita y_{st} is a function of various explanatory variables,

$$(1) \ln y_{st} = \beta_0 + Economy_{st} \beta_1 + Policy_{st} \beta_2 + Other_{st} \beta_3 + \varepsilon_{st}.$$

Typically, $Economy_{st}$ is measured by the unemployment rate, $Policy_{st}$ is measured by dummy variables indicating which policies have been passed, and $Other_{st}$ includes factors such as the minimum wage and the level of the Earned Income Tax Credit (EITC), all measured for state s at time t . The variable $Other_{st}$ also generally includes state fixed effects, time fixed effects, and perhaps even state-specific time trends and lags of the dependent variable.

Although these studies estimate seemingly similar versions of Equation 1, they have come to widely varying conclusions. For example, a frequently cited study by the Council of Economic Advisers (CEA 1997) attributes 44 percent of the 1993-96 caseload decline to economic conditions and 31 percent of the decline to welfare waivers. In contrast, another frequently cited study attributes more than two-thirds of the same decline to economic conditions and nothing to welfare waivers (Ziliak et al. 2000).

Several studies suggest that the sensitivity in results are due to differences in how the “caseload dynamics” in Equation 1 are specified, where caseload dynamics refers to how previous conditions impact the contemporaneous caseload. CEA (1999), updating the CEA (1997) study, finds that simply including a second lag of the unemployment rate reduces the role of the economy by about half when compared with a model with only one unemployment lag. Figlio and Ziliak (1999) attempt to reconcile the differences between CEA (1997) and Ziliak et al. (2000) and conclude that the different findings are primarily related to the inclusion of lagged regressors and lagged dependent variables. Bell’s (2002) and Blank’s (2002) recent literature reviews also point to dynamic issues as being crucial to understanding caseload changes. However, none of these studies provide any theoretical guidance to motivate the dynamic specification choices that are made.

A. A Stock-flow Model

To provide a theoretical basis for these specification choices, we specify an explicitly dynamic model. In particular, we begin with a model that views the contemporaneous

3. Studies in the recent strand of literature include CEA (1997), Levine and Whitmore (1998), CEA (1999), Figlio and Ziliak (1999), Moffitt (1999) Wallace and Blank (1999), Schoeni and Blank (2000), Ziliak et al. (2000), and MaCurdy, Mancuso, O’Brian-Strain (2002), and Grogger (2003). Bell (2002) and Blank (2002) provide reviews of the recent literature. Congressional Budget Office (1993) provides a list of earlier studies that examine the determinants of the caseload. Moffitt (1992) provides a more general review of the welfare literature.

caseload (a stock) as the result of previous flows onto and off of the caseload. Formally, consider a time-inhomogeneous, Markov Chain model,

$$(2) \quad S_t = \underset{(Q \times 1)}{M(x_t, \theta)} \underset{(Q \times Q)}{S_{t-1}} \underset{(Q \times 1)}{.}$$

The vector S_t contains the proportion of individuals in each of Q “states.” The matrix $M(x_t, \theta)$ describes how individuals transit between the states. The transition probabilities depend on time-varying explanatory variables x_t , such as the economy and policy, and a parameter vector θ .

We posit a state-space that distinguishes between those who are on aid and those who are off of aid, as well as between those who have been on aid for different numbers of periods.⁴ Specifically, we consider the model,

$$(3) \quad \begin{pmatrix} s_t^{r,1} \\ s_t^{r,2} \\ s_t^{r,3} \\ \vdots \\ s_t^{r,K} \\ s_t^n \end{pmatrix} = \begin{pmatrix} 0 & 0 & \dots & 0 & 0 & e(x_t, \theta) \\ c^1(x_t, \theta) & 0 & \dots & 0 & 0 & 0 \\ 0 & c^2(x_t, \theta) & \dots & 0 & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ 0 & 0 & \dots & c^{K-1}(x_t, \theta) & c^K(x_t, \theta) & 0 \\ 1 - c^1(x_t, \theta) & 1 - c^2(x_t, \theta) & \dots & 1 - c^{K-1}(x_t, \theta) & c^K(x_t, \theta) & 1 - e(x_t, \theta) \end{pmatrix} \begin{pmatrix} s_{t-1}^{r,1} \\ s_{t-1}^{r,2} \\ s_{t-1}^{r,3} \\ \vdots \\ s_{t-1}^{r,K} \\ s_{t-1}^n \end{pmatrix}$$

where s_t^{rk} is the proportion of individuals who have been recipients for k periods, s_t^n is the proportion of individuals who are nonrecipients, $c^k(x_t, \theta)$ is the continuation rate for those who are on aid for k periods (that is one minus the exit rate), and $e(x_t, \theta)$ is the entry rate. Implicitly, this model assumes that the continuation rate is constant after K periods, an assumption we return to below.

Equation 3, in conjunction with functional form assumptions for the entry rate and continuation rate, can be used to examine the impact of changing regressors on the welfare caseload. We first estimate models for the flows (the entry rate and the continuation rate) to obtain estimates of the parameter vector θ . Then, given an initial stock S_0 and any arbitrary path for the regressors $\{\check{x}_j\}_{j=1}^J$, we simulate the stock in period J as,

$$(4) \quad S_J = \left(\prod_{j=1}^J M(\check{x}_j, \theta) \right) S_0.$$

For example, we can estimate the role of the economy in the recent caseload decline by comparing the actual caseload path to a simulated caseload path in which the unemployment rate does not decline.

B. Implications for Conventional Stock Models

What are the implications of an explicitly dynamic stock-flow model (Equation 3) for specifying the conventional stock regressions (Equation 1)? One way to recover

4. See Haider, Klerman, and Roth (2003) for a more general specification that allows the probability of reentry to vary with time since last welfare receipt. They conclude that while models without reentry can be rejected in favor of models with reentry, the qualitative and quantitative findings regarding the role of the economy are robust to more general specifications. Therefore, our discussion here considers the simpler model that is sufficiently rich to make our substantive points.

Equation 1 is to assume that the entry rate function and all of the continuation rate functions in Equation 3 are identical. Denoting this common flow rate as $f(x_t)$ and letting y_t again denote the share of the population on aid ($y_t = \sum_k s^{tk}$), it is straightforward to see that Equation 3 simplifies to,

$$(5) \quad y_t = f(x_t).$$

Equation 1 can then be recovered by letting $f(x_t)$ be an exponential function of various explanatory factors and the error term, all entered linearly. This formulation provides no guidance regarding the dynamic structure of the caseload. Thus, we could include any explanatory variables thought appropriate, including lagged values of regressors and lagged values of the dependent variable.

The lack of dynamic structure in Equation 5, however, is due to the strong assumptions that we made. If we relax the assumption that the continuation and entry rate functions are identical while maintaining the assumption that all of the continuation rate functions were equal, Equation 3 simplifies to,⁵

$$(6) \quad y_t = e(x_t) + (c(x_t) - e(x_t)) y_{t-1}.$$

In this expression, the contemporaneous caseload now depends on past conditions, making the caseload an explicitly dynamic process.

To relate this equation back to the caseload models that have been used in previous studies (Equation 1), define $\tilde{c}(x_t)$ to be the continuation rate net of the entry rate ($\tilde{c}(x_t) = c(x_t) - e(x_t)$). Then, substituting this net continuation rate into Equation 6 and exploiting its recursive structure, we obtain the expression,

$$(7) \quad \begin{aligned} y_t &= e(x_t) + \tilde{c}(x_t) y_{t-1} \\ &= e(x_t) + \tilde{c}(x_t) e(x_{t-1}) + \tilde{c}(x_t) \tilde{c}(x_{t-1}) y_{t-2} \\ &= e(x_t) + \sum_{l=1}^{L-1} e(x_{t-l}) \prod_{m=0}^{l-1} \tilde{c}(x_{t-m}) + y_{t-L} \prod_{l=0}^{L-1} \tilde{c}(x_{t-l}), \end{aligned}$$

where L represents an arbitrary number of recursions.

The structure of Equation 7 has several direct implications for specifying caseload models that do not rely on lagged dependent variables, which we refer to as “static stock” models (for example, CEA 1997; CEA 1999; Bartik and Eberts 1999; Schoeni and Blank 2000; Blank 2001; Grogger 2003).

- If the (multiple) lagged caseload is to be excluded as a regressor, sufficient lagged regressors must be included (L must be large enough) to make the last term inconsequential.
- Interactions between regressors of different lags are likely to be important.
- It is not possible to derive the logarithmic relationship in Equation 1.

The intuition for these implications is straightforward. It is possible that much information about previous conditions (in other words, many lags) might be necessary

5. There are many justifications for allowing such state dependence in welfare receipt. On theoretical grounds, implicit contracts for work or fixed costs to entry and exit would cause state dependence. On empirical grounds, many studies distinguish between entry and exit and find that the processes behave differently (Moffitt 1992).

to describe the size of the current caseload. Interactions matter because, for example, bad economic conditions a few years ago will lead to a larger caseload today if the intervening years were also bad. A logarithmic relationship does not arise because the basic accounting identity—that this period’s caseload is equal to the sum of new entrants and those continuing on aid from last period—only applies in the levels.

The practical difficulty in applying these implications is that they suggest static stock models must include many lags of the explanatory variables and a complete set of interactions, yet the available time series component of the available data is relatively short. The actual number of lags that will be empirically important depends on functional form assumptions and parameter values for the flow rates. However, previous research (and results below) finds that the continuation rate is much higher than the entry rate, implying that the number of required lags is likely to be large (Moffitt 1992; Bane and Ellwood 1994).

Equation 7 also has implications for caseload models that include lagged dependent variables, which we refer to as “dynamic stock” models (for example, Ziliak et al. 2000). Specifically, the first equation demonstrates that the inclusion of a lagged dependent variable can substitute for the inclusion of many lagged explanatory variables. The intuition for this result is that the lagged aggregate caseload contains all necessary information about past conditions, implying that lagged regressors are no longer needed. However, this structural justification suggests a specification that is different from that used in previous dynamic stock studies: the dependent variable is the level of the per capita caseload (not the logarithm) and the lagged dependent variable should be entered alone and interacted with contemporaneous explanatory variables.

Although Equation 7 suggests that the inclusion of a lagged dependent variable is an analytic solution to requiring many lagged regressors, the result is not general. Instead, it depends on the assumption that the continuation rate functions were equal across length of time on aid, an assumption at odds with much of the previous literature.⁶ When we relax this assumption, Equation 3 implies that the share of the population on welfare is,

$$(8) \quad y_t = \sum_{k=1}^K s_t^{r,k} \\ = e(x_t)[1 - y_{t-1}] + \sum_{k=1}^K c^k(x_t) s_{t-1}^{r,k}.$$

Thus, with duration dependence, the duration-specific continuation rates ($c^k(x_t)$) enter the caseload regression as a linear combination with weights equal to the duration-specific share of individuals on aid ($s_{t-1}^{r,k}$). These weights are not fixed but instead vary with past values of the explanatory variables,

$$(9) \quad s_t^{r,k} = e(x_{t-k})[1 - y_{t-k-1}] \prod_{j=2}^{k-1} c^j(x_{t-j}).$$

Therefore, even in a model in which the flows are only a function of contemporaneous explanatory variables, an aggregate lagged dependent variable is not sufficient to

6. From an economic perspective, human capital depreciation or negative stigma associated with welfare could induce duration dependence. From an empirical perspective, many papers show clear evidence of duration dependence, even conditional on many covariates (Bane and Ellwood 1994).

eliminate the need for long lags of the explanatory variables (and their interactions) whenever there is duration dependence in the continuation rate.

III. The Data

Directly estimating a stock-flow model requires panel data on individuals, across sufficiently varying explanatory variables, for a sufficiently long time period, and for a sufficiently large sample. Appropriate national data do not appear to exist. Administrative, individual panel data are not collected at the national level. Available panel surveys such as the Panel Study of Income Dynamics and the Survey of Income and Program Participation appear to record welfare receipt with considerable error, to contain too few observations to estimate the transitions that are the focus of this study, and (in the case of the latter survey) to have panels that are short relative to the length of welfare spells.

Instead, we estimate our stock-flow models using administrative data from California's Medi-Cal Eligibility Determination System (MEDS).⁷ The MEDS provides a monthly roster of welfare participants in California from 1987 to the present. The MEDS is recorded as part of an on-going administrative process so biases associated with self-reports are not present. Importantly, there is significant diversity in economic conditions across California's counties. This diversity allows us to use an identification strategy that is similar to that used in the national literature (geographic and time series variation) to examine the role of economic conditions across California's 58 counties. Finally, California is a large state with more than 20 percent of the U.S. welfare caseload and more than 10 percent of the U.S. population; caseload trends in California comprise a significant share of the caseload trends in the United States.

The MEDS data have one major disadvantage in that they cover only a single state. Although identifying the impact of state-level policy is one of the motivations for the national literature, state-level policy only varies temporally in our data and we do not have a plausible strategy to separate policy changes from more general secular changes. Therefore, we concentrate on the impact of changing economic conditions.

The appendix discusses the details of our analysis file. In brief, we construct an analysis file by drawing a stratified random sample of approximately 3 percent of the full MEDS. Consistent with our focus on the effect of county level variation in the economy, the stratified sample is chosen to yield approximately equal numbers of persons in each of California's counties. This scheme results in an analysis file that contains a sample of 282,381 people who received cash assistance, comprising 487,641 spells and 10,966,420 person-months, during the years 1989–98 (our eventual sample period). Our basic unit of analysis throughout the paper is recipients rather than cases so that there exists a well-defined, longitudinal unit.⁸

7. Hoynes (2000) uses a different extract from the same underlying database.

8. Some of the aggregate literature uses the caseload as their unit of analysis rather than the recipient. Based on our comparisons (presented in earlier drafts of the paper and available from the authors) and those of others (Figlio and Ziliak 1999), the results are almost identical when using either dependent variable in the aggregate regressions.

In Figure 1, we present the aggregate monthly caseload computed from the MEDS-based analysis file, the official state caseload counts (based on county-level “CA237” reports), and the unemployment rate. The figure shows that the MEDS tracks the official caseload counts very well. The figure also shows that the caseload increased during the early 1990s and then declined during the latter 1990s, similar to the trend for the United States as a whole. At the peak of the welfare caseload in March 1995, there were approximately 2.7 million people receiving AFDC/TANF in California. In the last month of our sample period, December 1998, there are only 1.9 million people on aid, representing a 31 percent decline from the peak in March 1995. Turning to the unemployment rate, the figure shows that the unemployment rate increased then decreased, following a similar pattern to that of the caseload. In particular, the unemployment rate declined from 10 percent at its peak to 6 percent at the end of our sample period. Finally, the unemployment rate appears to lead the caseload. This empirical finding is consistent with lagged economic conditions having a strong impact on the current welfare caseload, as implied by a stock-flow model.

Table 1 presents the average monthly entry rate and continuation rate for two-year intervals between 1989 and 1997. These tabulations reveal several important characteristics of the data. First, the levels of the entry and continuation rates in Table 1 are quite different, suggesting that the contemporaneous caseload stock will depend on past conditions. The average monthly entry rate for those who were not on welfare in 1989–90 was 0.0032 and average monthly continuation rate for those who were on

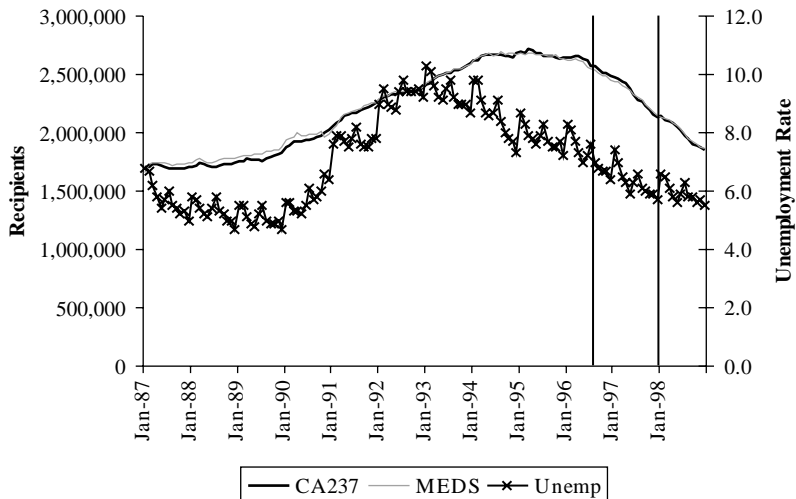


Figure 1
Welfare Recipients and Unemployment Rate in California

Note: Authors' tabulations from the MEDS, CA237, and the California unemployment rate. The CA237 is the official California welfare caseload. The MEDS represents an estimate of the caseload based on the 3 percent sample we analyze in this paper. The first vertical line represents the passage of the federal welfare reform legislation (PRWORA, August 1996) and the second vertical line represents the implementation of the California welfare reform (CalWORKS, January 1998).

Table 1
Short Term Spell Durations, 1989–97

Spell Start Period	Spells	Average Monthly Entry Rate	Average Monthly Continuation Rate by Duration			
			2–5 Months	6–11 Months	12–17 Months	18+ Months
1/89–12/90	70,721	0.0032	0.938	0.943	0.964	0.979
1/91–12/92	79,620	0.0037	0.942	0.950	0.968	0.982
1/93–12/94	80,863	0.0037	0.946	0.951	0.968	0.982
1/95–12/96	72,234	0.0031	0.942	0.949	0.962	0.977
1/97–12/97	29,862	0.0024	0.933	0.942	X	X

Source: Authors' tabulations from the MEDS data.

Note: The entry rate is calculated as the total number of entrants as a proportion of the population younger than age 50. An "X" indicates that the probability could not be calculated because of right-censoring. The entry rate represents that average monthly entry rate.

welfare between two and five months was 0.938.⁹ Second, the monthly continuation rate varies by duration, suggesting that a lagged dependent variable is not sufficient to capture the dynamics of the caseload. For example, the continuation rate for spells in months 2–5 is 0.938 in 1989–90, but the similar rate for spells lasting at least 18 months is 0.979; although these rates may appear similar, compounding them over six months suggests that someone just starting welfare has a 20 percent greater chance of leaving than someone who has been on for at least 18 months. Third, both the entry and continuation rates are counter-cyclical. The entry rate increased during the recession of the early 1990s (from 0.0032 to 0.0037) and then declines during the recovery (back to 0.0024).

IV. Reassessing Results from Conventional Stock Regressions

We begin by estimating conventional stock regressions that mimic those estimated in the national literature. Using the California MEDS data aggregated to the county/year level, we estimate the model,

$$(10) \quad \ln y_{jt} = \alpha + u_{jt}\beta + x_{jt}\phi + \gamma_t + \delta_j + \varepsilon_{jt},$$

9. For this and later analysis, we restrict the population at risk to be all individuals under the age of 50. We include the entire population under 50 because males can be on aid as children and participate in welfare via the smaller AFDC-Unemployed Parent program (AFDC-UP), which provides welfare benefits to two parent families in which the husband has recently lost a job.

where y_{jt} is the welfare recipients per capita, u_{jt} is the unemployment rate, x_{jt} is a vector of other potential regressors, γ_t is a time fixed effect, and δ_j is a county fixed effect, all for county j and year t .¹⁰ We estimate both static stock models (that include lags of the unemployment rate as regressors) and dynamic stock models (that also include a lagged dependent variable as a regressor).

We present the static stock results in Columns 1–4 of Table 2. The model with no lags of the unemployment rate (Column 1) implies that a 1 percentage point increase in the unemployment rate is associated with a 2.2 percentage point increase in the welfare caseload. To compare the results across models with different numbers of unemployment rate lags, we calculate the long-run impact of a permanent change in the unemployment rate by summing the various unemployment coefficients. The long-run impact increases as additional lags are added, from 2.2 percent (no lags), to 3.5 percent (one annual lag), to 4.7 percent (two annual lags), and then to 5.9 percent (three annual lags). Following previous studies, we also calculate the percent of the 1994–98 caseload decline that can be explained by the unemployment rate (see the appendix for details). The estimates imply that 20 percent (no lags), 37 percent (one lag), 36 percent (two lags), and 20 percent (three lags) of the caseload decline can be attributed to the declining unemployment rate. These results are qualitatively and quantitatively very similar to those obtained in the national literature, including the sensitivity to the number of included lags (CEA 1999).¹¹

The sensitivity to the inclusion of lags is related to a peculiar regularity that can be observed across these four models and in many previous studies. Specifically, the coefficient on the longest included lag is quantitatively the largest and highly statistically significant, while the shorter lags tend to be close to zero or even wrong signed, regardless of the number of lags that are included in the model.¹² These two empirical findings are related because, given that the longest included lag is always the largest, the calculation to assess the 1994–98 caseload decline is driven by a different unemployment rate change in each model. For example, the two-lag model is driven by the unemployment rate change from 1992–96 (9.4–7.4 percent, or –2.0 percentage point change) and the three-lag model is driven by the unemployment rate change from 1991–95 (7.7–7.8 percent, or +0.1 percentage point change). Thus, when assessing the role of the economy, the largest coefficient (the longest coefficient) is being multiplied by much different unemployment rate changes across the different specifications.

The analytic results from the stock-flow model offer an explanation for why the longest lag is largest. Specifically, the analytic results suggest that the static stock

10. Although the stock-flow model suggests that these regressions should be run in levels rather than in logarithms, we present logarithmic results to facilitate comparisons with the national literature. Analogous regressions in levels (not presented here) show similar patterns.

11. As a comparison to the national literature, the long-run effect of the economy with two annual lags is 5.4 percent (see CEA 1999, Model 1 in Table 2), as compared with our results of 4.7 percent.

12. This empirical regularity can be observed in CEA (1997), CEA (1999), Figlio and Ziliak (1999), Moffitt (1999), Wallace and Blank (1999), and Blank (2002). Some previous authors have suggested that lagged unemployment might be more important than contemporaneous unemployment “because welfare recipients are likely to be the last ones hired during an economic recovery and thus may not instantaneously move from welfare to work” (see Figlio and Ziliak, 1999, p. 32–33). However a natural extension of this argument is that welfare recipients are also the *first* to be fired during economic downturns; over the business cycle, these effects would tend to be offsetting.

Table 2
Welfare Stock Regressions Using Annual Data

Regressors	1	2	3	4	5	6	7	8	9	10	11
UR-0	0.022 (0.007)	-0.001 (0.009)	-0.008 (0.009)	-0.003 (0.009)	0.050 (0.009)	0.019 (0.015)	0.026 (0.016)	0.028 (0.003)	0.019 (0.004)	0.018 (0.004)	0.020 (0.004)
UR-1		0.035 (0.009)	0.013 (0.010)	0.006 (0.010)	0.093 (0.009)	0.074 (0.018)	0.051 (0.019)		0.013 (0.004)	0.009 (0.005)	0.006 (0.005)
UR-2			0.042 (0.008)	0.026 (0.009)		0.075 (0.013)	0.079 (0.018)			0.007 (0.004)	0.001 (0.005)
UR-3				0.030 (0.008)			0.029 (0.014)				0.014 (0.004)
Int(UR-0, UR-1)					-0.004 (0.0004)	-0.002 (0.0008)	-0.008 (0.002)				
Int(UR-0, UR 2)						-0.0002 (0.001)					
Int(UR-0, UR 3)							0.004 (0.004)				
Int(UR-1, UR 2)						-0.003 (0.001)					
Int(UR-1, UR 3)							0.003 (0.005)				
Int(UR-2, UR-3)							-0.008 (0.002)				
Dependent variable—1								0.976 (0.023)	0.967 (0.023)	0.958 (0.023)	0.951 (0.023)
R-squared	0.9676 20.5%	0.9686 36.9%	0.9700 35.6%	0.9707 20.4%	0.9752 71.9%	0.9772 71.5%	0.9781 66.7%		0.9927 61.8%	0.9928 69.8%	0.9930 41.1%
94–98 decline attributable to UR											
Long-run effect of permanent UR change	0.022	0.035	0.047	0.059	0.079	0.095	0.104	1.17*	0.99*	0.84*	0.82*

Source: Authors' tabulations from the MEDS data.

Note: All models are estimated on data aggregated to the county/year level, include county and time fixed effects, and use data for 1988–98. Standard errors are in parentheses. The long-run effect is the log-point impact of a permanent change in the unemployment rate; see the text for further details. Int(A, B) represents an interaction between A and B. To evaluate the long-run effect, we assume that the unemployment rate changes from 7 to 8 percent. *These long-run effects are difficult to interpret and are only reported for completeness.

models suffer from omitted variables bias because long lags of the explanatory variables and interactions between the lags are likely to be necessary, but are not included. This omitted variables bias can explain the empirical peculiarity because it can be shown that omitted lags of the explanatory variable will likely be most correlated with the longest included lag.¹³ Simply adding more unemployment rate lags to these models to static stock models is problematic, however, because of the relatively short available time series.

As further evidence that the static model is misspecified, we reestimate the models but include interactions among the lagged explanatory variables (see Columns 5–7 in Table 2). The interactions are highly jointly significant in all three of the models, with *F*-tests for excluding all interactions producing *p*-values well under 0.0001. Moreover, the measured importance of the economy increases substantially. By including complete sets of first-order interactions among the unemployment rate and its lags, the role of the economy increases from 36.9 (Column 2) to 71.9 percent (Column 5) for the one-lag model, from 35.6 (Column 3) to 71.5 percent (Column 6) for the two-lag model, and from 20.4 (Column 4) to 66.7 percent (Column 7) for the three-lag model.

We present results for the dynamic stock models in Columns 8–11 of Table 2. The unemployment coefficients are similar with and without the lagged dependent variable (for example, Column 1 versus Column 8), and the coefficients on the lagged dependent variable is close to one and highly significant. Because of the large lagged dependent variable coefficient, the long-run impacts of the unemployment rate are substantially larger.¹⁴ Again, we also compute the percent of the 1994–98 caseload decline that can be attributed to the economy (see the appendix for details). We find that the declining unemployment rate explains 62 percent of the caseload decline for the model that includes no lags, 73 percent in the one-lag model, 70 percent in the two-lag model, and 41 percent in the three-lag model.¹⁵ The longest included lag is not always the largest in these specifications, but the importance of the economy is still highly sensitive to the number of lags chosen.

The dynamic stock results are suspect for many reasons. On analytic grounds, a stock-flow model suggests that a lagged dependent variable is only an appropriate reduced-form solution when there is no duration dependence. Such an assumption is clearly rejected by previous studies and by our data. On empirical grounds, these dynamic stocks are subject to two concerns. As recognized by previous authors but not always addressed in estimation, a lagged-dependent variable in combination with the fixed effects identification strategy suggests that the estimates are subject to

13. It is straightforward to show that this claim is true for the case where the truncated explanatory variable follows an AR(1) process. For that case, in fact, it is *only* the last lag that is biased. Pakes and Griliches (1984) provide more general results on truncating lag structures. It is also straightforward to show that omitting interactions has the same impact for the case where the lagged independent variable follows an AR(1) process; the intuition for this result is not as readily apparent.

14. These long-run estimates represent the log-point increase in recipients per capita that would be associated with a one-percentage point increase in the unemployment rate. They are calculated as $\beta/(1-\rho)$, where β is the coefficient on the unemployment rate (or the sum of the unemployment rate and its lags) and ρ is the coefficient on the lagged dependent variable. The estimates are difficult to interpret because ρ is so large; we present them mainly for completeness.

15. These results are also very similar to the national literature. For example, Figlio and Ziliak's (1999) preferred specifications attribute 68 and 75 percent of the caseload decline to the economy.

Nickell bias (Nickell 1981). Importantly, assuming that the unemployment rate increases the welfare caseload, Nickell bias is likely to cause the estimates on the unemployment rate to be too high. Perhaps even more problematic is the well-known concern that lagged dependent variable models are biased if the errors are serially correlated (Greene 2002). This is almost certainly the case. For example, any policies relevant to welfare recipients that are omitted from the regression are likely to be positively correlated over time. Thus, it is likely that the large estimates produced by the dynamic stock methods are artifacts of the estimation method.

V. Results from a Stock-flow Model

The previous section has shown that the aggregate regressions are consistent with the implications of our stock-flow model. In this section, we directly estimate a stock-flow model and perform simulations to estimate the impact of the economy on the caseload.

A. Modeling the Flow Relationships

The key element for the simulation model is the relationship between economic conditions and the flows onto and off of welfare. Because the MEDS data include information only for those on welfare, we estimate our model for the entry rate using a grouped-data equivalent of the individual-level, logit model used in much of the literature (Blank and Ruggles 1996; Hoynes 2000). We calculate the entry rate for county j in month t , e_{jt} , as the ratio of the number of entrants observed in the MEDS relative to the number of people at risk of going on aid. We then estimate a grouped-data logit model at the county-month level that includes the unemployment rate and fixed effects for time and county,

$$(11) \quad \ln \frac{e_{jt}}{1 - e_{jt}} = \alpha_e + \beta_e u_{jt} + \gamma_t + \delta_j + \varepsilon_{jt}.$$

Rather than including a full set of dummy variables for each month of our data, we include a piece-wise linear spline (by year and that is not continuous) to capture a general time trend and calendar month dummies (a dummy for January, February, etc.) to capture seasonal variation.

We estimate the continuation rates $C^K(x_t)$ using individual-level data. Let k_{ijt} be the number of months an individual is on aid and C_{ijt} be an indicator variable equal to one if an individual leaves aid, both for individual i in county j at time t . Consider the model,

$$(12) \quad \Pr[C_{ijt} = 1] = f(\alpha_c + \beta_c u_{jt} + \gamma_t + \delta_j + g_c(k_{ijt})),$$

where $g_c(k_{ijt})$ includes dummy variables for the first six months individuals are on aid and thereafter a quartic in k_{ijt} .¹⁶ Given the large data set, we specify f to be a linear

16. The sensitivity of these and later assumptions are examined in detail in Haider, Klerman, and Roth (2003). For example, the model is not sensitive to allowing the effect of the unemployment rate to vary with duration, the specification for time effects and for the duration function is consistent with the underlying data, and the results are not sensitive to allowing for a more flexible specification.

function, implying that Equation 12 is simply a linear probability model. Finally, we modify the basic specification by adopting a similar time structure as described for the entry rate model, a discontinuous piece-wise annual spline with calendar month dummies.

One complication is that we have data only on current welfare receipt for any particular month. Therefore, for individuals who receive welfare in the first month of the data (January 1987), we do not know how long they have received aid. We address this standard left-censoring problem by assuming that the continuation rate is constant after K months (see Equation 3). Specifically, if we discard the first K months of data, we can then place all welfare recipients into the appropriate state (received aid for one month, two months, . . . , 23 months, or at least 24 months) in all subsequent months. We set K to be 24 months for the results we present here, a specification that is supported by the data. Thus, we drop the monthly data for 1987–88 and use data only for 1989–98 in estimation.

B. Estimates with Monthly Data

We present the results for the entry and continuation models in Table 3 using monthly data from January 1989 to December 1998, as well as results for the static stock model using monthly data. We present results for models with two, five, and eleven monthly lags of the unemployment rate. The static stock regressions (Columns 1 to 3) reveal the same pattern as was observed with the annual data (the longest lag is always the largest).

In contrast, the entry models (Columns 4–6 in Table 3) reveal a much different pattern. The contemporaneous unemployment rate and initial lags are the largest, of the expected sign, and significant for all three of the logistic regressions. Moreover, the results indicate that only a few monthly lags (perhaps two or three) are needed to capture the variation in the data.

The results are just as striking for the continuation rate regressions (Columns 7–9 in Table 3). Again, current unemployment and the initial lags tend to be large, of the expected sign, and statistically significant, and the results indicate that few monthly lags are needed to capture the variation in the data.

These estimates show that the peculiar results regarding lags observed in the stock regressions are not observed in the flow regressions and that far fewer lags are needed to capture the underlying flow relationships. These results suggest that the complicated lag structure in the stock regressions could simply be due to the stock-flow process itself. Importantly, these findings also suggest that far shorter time series will be needed to obtain precise estimates when flow data are used.

C. Recovering the Stock Relationships from the Flow Relationships

The main focus of this paper is the implications of these flow relationships for how the caseload changes. We examine this relationship by using the flow estimates to calculate the probability that a person transits between the states of being on aid and off of aid (the elements of the transition matrix M) for various counterfactual histories. These probabilities are then combined using the stock-flow model to simulate how the caseload evolves over time (see Equation 4).

Table 3
Stock, Entry and Continuation Regressions Using Monthly Data

Regressors	Static Stock Regressions (OLS)			Probability of Entry (Grouped Logit)			Probability of Continuation (OLS: Coefficients & Standard Errors × 100)		
	1	2	3	4	5	6	7	8	9
UR-0	0.003 (0.002)	0.007 (0.002)	-0.006 (0.002)	0.030 (0.006)	0.036 (0.006)	0.022 (0.007)	0.121 (0.009)	0.115 (0.009)	0.097 (0.011)
UR-1	-0.001 (0.003)	0.001 (0.003)	0.006 (0.003)	0.019 (0.008)	0.024 (0.009)	0.031 (0.009)	-0.017 (0.013)	-0.034 (0.014)	-0.037 (0.014)
UR-2	0.008 (0.002)	0.001 (0.003)	0.002 (0.003)	-0.020 (0.006)	-0.040 (0.009)	-0.040 (0.009)	-0.003 (0.009)	0.065 (0.014)	0.081 (0.014)
UR-3		0.003 (0.003)	0.003 (0.003)		0.010 (0.009)	0.013 (0.009)		-0.081 (0.014)	-0.078 (0.014)
UR-4		-0.002 (0.003)	0.001 (0.003)		0.006 (0.009)	0.017 (0.009)		0.049 (0.014)	0.038 (0.014)
UR-5		0.009 (0.002)	0.005 (0.003)		0.006 (0.006)	-0.013 (0.009)		-0.026 (0.010)	-0.002 (0.014)
UR-6			0.001 (0.003)			0.014 (0.009)			-0.030 (0.014)
UR-7			0.002 (0.003)			0.001 (0.009)			-0.027 (0.014)
UR-8			0.001 (0.003)			-0.008 (0.009)			0.064 (0.014)
UR-9			0.001 (0.003)			0.009 (0.008)			-0.016 (0.014)
UR-10			-0.001 (0.003)			0.012 (0.008)			-0.020 (0.014)
UR-11			0.013 (0.002)			0.003 (0.007)			0.023 (0.011)
R-squared	0.9669	0.9671	0.9677	0.8216	0.8222	0.8232	0.0096	0.0096	0.0096

Source: Authors' tabulations from the MEDS.

Note: We use monthly data for the period January 1989 to December 1998 for each set of models, with the lags referring to monthly lags. All models contain county fixed effects and a flexible spline in time. See the text for further details. Standard errors are in parentheses.

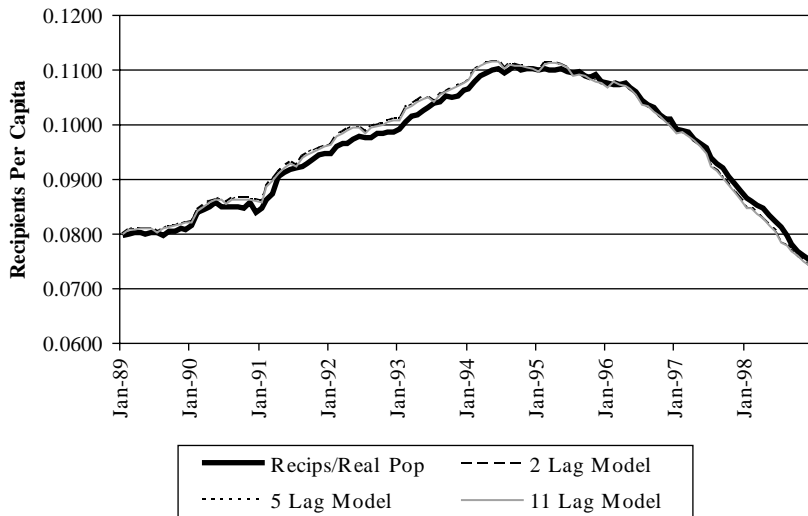


Figure 2

The Actual and Simulated Per Capita Welfare Caseload

Note: Authors' tabulations from the MEDS. The lower line (with x's) represents the real recipients per capita in California. The other three lines, which lie on top of each other, represent the simulated recipients per capita using the stock-flow model. We present results for the model that includes two, five, and eleven lags of the unemployment rate.

We first present simulations for the actual history of the unemployment rate path in Figure 2 to demonstrate the fit of the model. We perform these simulations for flow models in which we include two, five, and eleven monthly lags, and graph these results along with the actual recipients per capita. The stock-flow model captures the major features of the data. The main difference between the actual recipients per capita and the predicted estimates is that the predicted estimates are too high for the middle of the sample period and decline too quickly towards the end of the sample period.

To answer the question "How much of the caseload decline (from its peak) is due to economic conditions?" we compare the simulation based on the actual time and unemployment rate path with a simulation where we assume a different unemployment rate path. We consider two counterfactual histories of the unemployment rate: (1) an unemployment rate path that follows its actual path until the unemployment rate peak (January 1993) and then remains constant, and (2) an unemployment rate path that follows its actual path until the caseload peak (March 1995) and then remains constant. Our preferred counterfactual is the first because half of the decline in the unemployment rate occurred before the caseload peak: the unemployment was 10.3 percent in January 1993, 7.8 percent in March 1995, and 5.5 percent in December of 1998. Thus, by March 1995, economic conditions would have already put significant downward pressure on the welfare caseload. This pressure can be observed in Figure 2 in the significant slowdown of the caseload growth from January 1993 to March 1995. The second counterfactual implicitly overlooks this pressure.

Figure 3 (with the estimates summarized in Table 4) presents the simulations for the counterfactual where the unemployment rate remains constant after January 1993. As expected, the caseload does not decline as much for each of the counterfactual histories when compared to the simulated caseload decline with the actual unemployment rate. The two-, five-, and eleven-lag models imply that, because of the estimated time fixed effects, the caseload would have declined by approximately 18 percent even if the unemployment rate would have remained constant. The time fixed effects likely capture unmeasured changes in economic conditions and policy. When compared to the 33 percent decline that was actually observed, these models imply that approximately 47 percent of the caseload decline can be attributed to the declining unemployment rate. These are our preferred estimates because of their stability and because they capture the entire improvement of the economy.

We also perform similar simulations for the counterfactual unemployment rate that remains constant after March 1995 for the two-, five-, and eleven-lag models. We summarize the results for these simulations in Table 3. As expected, these estimates imply a smaller role for the economy, with unemployment rate explaining 12–23 percent of the total caseload decline. This counterfactual, however, ignores the fact that more than half of the unemployment rate decline occurred in the two years before March 1995.

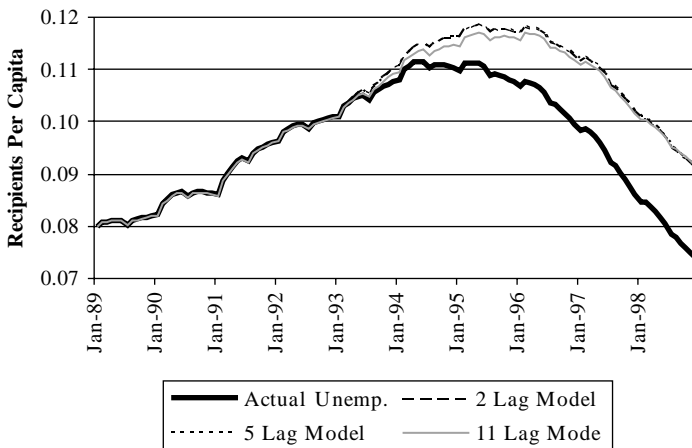


Figure 3

The Simulated Welfare Caseload in California—Holding the Unemployment Rate Constant at its Peak Value

Note: Authors' tabulations from the MEDS. The four lines correspond to simulation the number of recipients per capita based on the actual unemployment rate (using the two lag model) and based on holding the unemployment rate (and its lags) constant after January 1993 using the two-lag, five-lag, and eleven-lag models.

Table 4
Simulation Results for the Per Capita Caseload

	Monthly lags in flow models		
	2 lags	5 lags	11 lags
Simulations with actual unemployment rate path			
Simulated March 1995 level	0.107	0.107	0.107
Simulated December 1998 level	0.071	0.071	0.071
Simulated percent decline	-33.5%	-33.4%	-33.4%
Simulations with counterfactual unemployment rate path			
(1) Unemployment rate remains constant after unemployment rate peak (1/93)			
Simulated December 1998 level	0.087	0.088	0.088
Simulated percent decline	-18.1%	-17.7%	-17.5%
Decline due to economic conditions	46.1%	47.0%	47.4%
(2) Unemployment rate remains constant after caseload peak (3/95)			
Simulated December 1998 level	0.075	0.077	0.079
Simulated percent decline	-29.4%	-27.7%	-25.6%
Decline due to economic conditions	12.2%	17.1%	23.3%

Source: Authors' tabulations from the MEDS.

Note: Simulations are based on the stock-flow model developed in Equations 14–18. All calculations are based on monthly data for the period January 1989 to December 1998. See the text further details.

VI. Conclusions

This paper reconsiders the methods used in the national literature to assess the causes of the recent welfare caseload decline. The literature has reached widely varying conclusions about the causes of the decline and suggested that the varying conclusions arise from differences in the specification of dynamics. To shed light on these specification choices, we began with an explicitly dynamic model of individual flows onto and off of welfare. We then presented a series of analytical and empirical results that suggest that previous methods are likely to yield biased estimates. Finally, we developed, estimated, and simulated an empirical model based on the underlying flows and provide estimates for the role of the economy in determining California's caseload decline.

The empirical results provide strong support for the stock-flow approach. Our model provides a plausible explanation for peculiar and sensitive results in the previous literature, as well as successfully predicts that interactions are likely to be important. Furthermore, while the stock regressions appear to require a large number of annual lags of the explanatory variables, the flow regressions require only a few monthly lags of the explanatory variables. Given the short available time-series, this could be a significant advantage for estimation. Finally, our preferred estimates suggest that approximately half of the California caseload decline can be attributed to

changing economic conditions, an estimate that is appreciably larger than that obtained from static stock estimates.

Our preferred results should be interpreted with caution. First, in comparing California with the rest of the nation, the 1990s recession was deeper, welfare reforms were passed later, and the reforms that were passed were weaker (see Klerman et al. 2000; Grogger, Karoly, Klerman 2003). Thus, the role for the economy may be greater in California than in other states. Second, several other studies find that the unemployment rate does not adequately capture the role of the economy (for example, Hoynes 2000; Haider, Klerman, and Roth 2003). This latter concern suggests that our estimate for the role of the economy would be too low.

The results from this paper have implications beyond measuring the impact of economic conditions on the welfare caseload. The implications regarding lagged economic conditions equally apply to other explanatory variables. For example, consider a one-time policy change that caused the entry rate to decline. Such a change could cause the caseload stock to decline for several years in a stock-flow model.¹⁷ Thus, a conventional differencing identification strategy is likely to underestimate the effect of the policy change, particularly when differencing over short time periods. Such lagged policy effects have been largely ignored in the literature. In addition, such stock-flow concerns are likely to be important when evaluating many other economic outcomes. For example, Schoeni (2001) demonstrates that the literature examining the changing food stamp caseload exhibits many of the same empirical patterns as observed in the welfare literature.

Appendix

A. Calculating the Impact of Economic Conditions

Define $\hat{y}(u_a, \gamma_b)$ to be the predicted welfare recipients per capita based on Equation 1, with the unemployment rate for year a and the time effect associated with year b ,

$$(A1) \quad \hat{y}(u_a, \gamma_b) = \exp[\hat{\alpha} + u_a \hat{\beta} + \hat{\gamma}_b]$$

We define the impact of economic conditions for the static stock model to be

$$(A2) \quad \Delta_{econ}^s = \frac{[\hat{y}(u_{1998}, \hat{\gamma}_{1994}) - \hat{y}(u_{1994}, \hat{\gamma}_{1994})] / \hat{y}(u_{1994}, \hat{\gamma}_{1994})}{(y_{1998} - y_{1994}) / y_{1994}} \\ = \frac{\exp[\hat{\beta}(u_{1998} - u_{1994})] - 1}{(y_{1998} - y_{1994}) / y_{1994}}$$

The expression for the dynamic stock model takes into account that the impact of a change in the unemployment rate between 1994 and 1995 [$\hat{\beta}(u_{1995} - u_{1994})$] will have an additional impact between 1995 and 1996 [$\hat{\beta}(u_{1995} - u_{1994})$], $\hat{\rho}$ where $\hat{\rho}$ is the coefficient on the lagged dependent variable. Thus, the similar expression for the dynamic stock case is,

17. See Haider and Klerman (2004) for additional development of this idea. See Danielson and Klerman (2004) for empirical support for the importance of lagged policy changes.

$$(A3) \quad \Delta_{econ}^D = \frac{\exp[F] - 1}{(y_{1998} - y_{1994}) / y_{1994}}$$

where

$$(A4) \quad F = \hat{\beta}(1 + \hat{\rho} + \hat{\rho}^2 + \hat{\rho}^3)(u_{1995} - u_{1994}) + \hat{\beta}(1 + \hat{\rho} + \hat{\rho}^2)(u_{1996} - u_{1995}) + \dots \\ + \hat{\beta}(u_{1998} - u_{1997})$$

B. The MEDS Data

The Medi-Cal Eligibility Determination System (MEDS) is a monthly roster of all individuals eligible for Medi-Cal, California's Medicaid program that is used for administrative purposes. Because welfare recipients are categorically eligible for Medi-Cal and that source of eligibility is noted, MEDS provides a monthly roster of the welfare population in California. See Haider et al. (2000) for more details concerning the MEDS.

To avoid some small sample problems, we aggregate California's five smallest counties into a single "county" for analysis purposes. The five smallest counties are Alpine, Colusa, Modoc, Mono, and Sierra; combined, their welfare population represents well under one percent of the state's welfare population. We perform all of our analyses on these 53 counties and one county group.

Previous research indicates that there is considerable "churning" onto and off of welfare in the MEDS data. This churning is likely due to administrative record keeping rather than "real" entrances and exits (Hoynes 2000). To mitigate such concerns, we recode one-month spells onto and off of aid as not having occurred, following Hoynes (2000).

In addition to the MEDS, we also rely on various data sets that are publicly available. We use the CA237, the official monthly caseload reports from the counties to the California Department of Social Services; these data are described in Haider et al. (2000). We use Intercensal Population Estimates for each county, generated by the U.S. Bureau of the Census. For all of the estimates presented in this paper, we consider the population at risk of being on aid to be everyone under the age of 50. The population estimates are only available by year, so we perform a simple linear interpolation to obtain monthly data. Finally, we use local area unemployment estimates produced by the U.S. Department of Labor to proxy for economic conditions.

References

- Boskin, Michael, and Frederick Nold. 1975. "A Markov Model of Turnover in Aid to Families with Dependent Children." *Journal of Human Resources* 10(4):467-81.
- Bane, Mary Jo, and David Ellwood. 1994. *Welfare Realities: From Rhetoric to Reform: Preface*. Cambridge, Mass.: Harvard University Press.
- Bell, Stephen. 2002. "Why Are Welfare Caseloads Falling?" Urban Institute Discussion Paper 01-02.
- Blank, Rebecca and Patricia Ruggles. 1996. "When Do Women Use AFDC and Food Stamps? The Dynamics of Eligibility vs. Participation." *Journal of Human Resources* 31(1):57-89.
- Blank, Rebecca. 2001. "What Causes Public Assistance Caseloads to Grow?" *Journal of Human Resources* 36(1):85-118.

- . 2002. "Evaluating Welfare Reform in the United States." *Journal of Economic Literature* 15(4):1105–66.
- Congressional Budget Office. 1993. "Forecasting AFDC Caseloads, with an Emphasis on Economic Factors." Staff memorandum. July.
- Council of Economic Advisors. 1997. "Technical Report: Explaining the Decline in Welfare Receipt, 1993–96." *A Report by the Council of Economic Advisors* May.
- . 1999. "Technical Report: The Effects of Welfare Policy and the Economic Expansion on Welfare Caseloads: An Update." *A Report by the Council of Economic Advisors*, August.
- Figlio, David, and James Ziliak. 1999. "Welfare Reform, the Business Cycle, and the Decline in AFDC Caseloads." In *Economic Conditions and Welfare Reform*, ed. Sheldon Danziger, 17–48. Kalamazoo, Mich.: W. E. Upjohn Institute for Employment Research.
- Greene, William. 2000. *Econometric Analysis*. Upper Saddle River, N.J.: Prentice Hall, 4th Edition.
- Grogger, Jeffrey. 2003. "The Effects of Time Limits, the EITC, and Other Policy Changes on Welfare Use, Work, and Income among Female-Headed Families." *Review of Economics and Statistics* 85(2):394–408.
- Grogger, Jeffrey, Lynn Karoly, and Jacob Alex Klerman. 2002. *Consequences of Welfare Reform: A Research Synthesis*. Santa Monica, Calif.: RAND MR-1564-DHHS.
- Haider, Steven J., and Jacob Alex Klerman. 2004. "Dynamic Properties of the Welfare Caseload." *Labour Economics*. Forthcoming.
- Haider, Steven, Jacob Alex Klerman, Jan Hanley, Laurie McDonald, Elizabeth Roth, Liisa Hiatt, and Marika Suttorp. 2000. "Welfare Reform in California: Design of the Impact Analysis, Preliminary Investigations of Caseload Data." MR-1266.0/1. Santa Monica, Calif.: RAND.
- Haider, Steven, Jacob Alex Klerman, and Elizabeth Roth. 2003. "The Relationship between the Economy and the Welfare Caseload: A Dynamic Approach." *Research in Labor Economics* 22:39–69.
- Heckman, James, and James Walker. 1990. "The Relationship between Wages and Income and the Timing and Spacing of Births: Evidence from Swedish Longitudinal Data." *Econometrica* 58(6):1411–41.
- Hoynes, Hilary Williamson. 2000. "Local Labor Markets and Welfare Spells: Do Demand Conditions Matter?" *Review of Economics and Statistics* 82(3):351–68.
- Hutchens, Robert. 1981. "Entry and Exit Transitions in a Government Transfer Program: The Case of Aid to Families with Dependent Children." *Journal of Human Resources* 16(2):217–37.
- Klerman, Jacob Alex, Gail L. Zellman, Tammi Chun, Nicole Humphrey, Elaine Reardon, Donna Farley, Patricia A. Ebener, Paul Steinberg. 2000. *Welfare Reform in California: State and County Implementation of CalWORKs in the Second Year*. MR-1177-CDSS. Santa Monica, Calif.: RAND.
- Klerman, Jacob Alex, and Caroline Danielson. 2004. "Why Did the Welfare Caseload Decline?" WR-167. Santa Monica, Calif.: RAND.
- Levine, Phillip, and Diane Whitmore. 1998. "The Impact of Welfare Reform on the AFDC Caseload" *National Tax Association Proceedings 1997*, 24–33.
- MaCurdy, Thomas, David Mancuso, and Margaret O'Brien-Strain. 2002. "Does California's Welfare Policy Explain the Slower Decline of its Caseload?" Public Policy Institute of California Report.
- Moffitt, Robert. 1992. "Incentive Effects of the U.S. Welfare System: A Review." *Journal of Economic Literature* 30(1):1–61.
- . 1999. "The Effect of Pre-PRWORA Waivers on AFDC Caseloads and Female Earnings, Income, and Labor Force Behavior." In *Economic Conditions and Welfare*

- Reform*, ed. Sheldon Danziger, 91–118. Kalamazoo, Mich.: W. E. Upjohn Institute for Employment Research.
- Moffitt, Robert, and Michael Rendall. 1995. “Cohort Trends in the Lifetime Distribution of Female Family Headship in the United States, 1968–1985.” *Demography* 32(3):407–24.
- Nickell, Stephen. 1981. “Biases in Dynamic Models with Fixed Effects.” *Econometrica* 49(6):1417–26.
- Pakes, Ariel, and Zvi Griliches. 1984. “Estimating Distributed Lags in Short Panels with an Application to the Specification of Depreciation Patterns and Capital Stock Constructs.” *Review of Economic Studies* 51(2):243–62.
- Schoeni, Robert. 2001. “Comment on Currie and Grogger, Explaining Recent Declines in Food Stamp Program Participation.” In *Brookings and Wharton Papers on Urban Affairs*, ed. William G. Gale and Janet Rothenberg Pack. Washington, D.C.: Brookings Institution Press.
- Schoeni, Robert, and Rebecca Blank. 2000. “What Has Welfare Reform Accomplished? Impacts on Welfare Participation, Employment, Income, Poverty, and Family Structure.” National Bureau of Economics Research Working Paper 7627.
- Wallace, Geoffrey, and Rebecca Blank. 1999. “What Goes Up Must Come Down?” In *Economic Conditions and Welfare Reform*, ed. Sheldon Danziger, 49–90. Kalamazoo, Mich.: W. E. Upjohn Institute for Employment Research.
- Ziliak, James, David Figlio, Elizabeth Davis, Laura Connolly. 2000. “Accounting for the Decline in AFDC Caseloads: Welfare Reform or Economic Growth?” *Journal of Human Resources* 35(3):570–86.