The Interaction of Welfare-Use and Employment Dynamics In Rural and Agricultural California Counties

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Abstract

Using both monthly aggregate county-level data and monthly individual-level data on welfare participation in California from 1985 to 1997, we show that welfare use patterns in rural and agricultural counties differ from those in urban counties. We also explain variation in welfare dynamics between various types of counties, focusing on labor market structure. Our research combines several administrative data sets in novel ways that make it possible to describe county and individual-level welfare and employment dynamics. Our results indicate that the impact of the 1996 federal welfare reforms is likely to vary systematically by type of county according to their distinct welfare-use and employment patterns. As a result, policymakers may want to tailor welfare policies and implementation strategies to county conditions to increase the effectiveness of the new welfare legislation in facilitating exits from welfare to work.

The existing welfare system was dramatically reformed in 1996 by the federal Personal Responsibility and Work Opportunity Act. Families are no longer guaranteed public assistance for as long as they remain below a certain income threshold. The new cash assistance program, TANF (Temporary Assistance to Needy Families), has a five-year cumulative time limit for welfare receipt. The program aims to facilitate welfare exits through work by requiring participation in work activities after two years of welfare receipt, and reducing funding for states without a large enough share of their caseload engaged in work activities.

Considering TANF's emphasis on work-related welfare exits, it is clear that local economic conditions are a major determinant in TANF's success in facilitating these exits. Although it is known that a change in employment status is a major route off welfare, most welfare literature has neglected the role of local labor markets on welfare exits. In this paper, differences in local labor markets across different kinds of areas (i.e., urban, rural, agricultural, mixed) are examined, and the effect of these differences on welfare dynamics are assessed. The variation in the interaction of employment and welfare dynamics by type of county suggests that welfare reform will affect county types differently. Recognizing these differences can help policymakers tailor policies to regions.

Overview and Summary

Welfare-use patterns in rural and agricultural counties differ significantly from those in urban counties in California. A higher percentage of the population is on aid in agricultural and rural counties. There is also more cycling on and off welfare in these counties, so a larger portion of the welfare caseload both enter and exit welfare each year. Considering the greater amount of cycling on and off welfare at the aggregate level in nonurban counties, it is not surprising that we also observe that a welfare recipient in either a rural or agricultural county has, on average, both more and shorter welfare spells (lengths of time on welfare) than a welfare recipient in an urban county. Therefore, a person in an agricultural or rural county is more likely than a person in an urban county to go on welfare at any time; however, once on welfare, she is more likely to exit welfare before an urban welfare recipient who began welfare at the same time.

The pattern of cycling on and off welfare in nonurban counties is primarily the result of substantial seasonality in welfare accessions and terminations. We find that, holding county types constant, the typical welfare recipient in an agricultural or rural county is more likely than the typical welfare recipient in an urban county to enter welfare in the winter months and to exit in the summer months.[1]

Employment dynamics drive the differences in welfare-use patterns among county types, as employment patterns mirror the welfare-use ones. Unemployment, like welfare participation, is both higher and more cyclical in agricultural and rural counties than in urban counties. Using both aggregate county-level data on welfare accessions and terminations and individual-level data on terminations, we find that a substantial amount of the differences in welfare dynamics between urban counties and agricultural and rural counties can be explained by agricultural employment in agricultural counties and various nonagricultural forms of employment in rural counties.

The remainder of this paper elaborates on these themes. We begin with a review of the articles that explore labor market effects on welfare use. We then develop a typology of four kinds of California counties based on population density and agricultural employment: *urban*, *agricultural*, *rural*, and a residual category of *mixed*. California counties, we suggest, are worth studying in their own right because they are so big and so diverse, and they comprise a significant fraction of the total welfare population in America. If the fifteen agricultural counties in

California were a state, it would have a larger population than twenty-one American states,[2] and if the seventeen rural counties in California were a state, its population would be about the same or larger than the population in seven other states.[3] The total welfare population in California is about one-fifth of the nation's total, and it averaged over 2.3 million people each month during 1997. The number of persons on welfare in agricultural counties alone during each month of 1997 averaged over 325,000.

After developing the classification of counties, we provide a description of aggregate welfare and employment dynamics in each type of county. We show that nonurban counties in California have a pronounced seasonality in welfare entrances and exits. This seasonality appears to be correlated with agricultural employment in the agricultural and mixed counties and with retail and other forms of nonagricultural employment in rural counties.

We then develop a theoretical model of welfare entrances and exits that guides us in our aggregate and micro-level specifications linking welfare use to employment patterns. Our model considers entrances and exits from welfare to be the result of a stochastic process among the relevant at-risk population in which different sub-populations have different chances of entering or exiting welfare. These chances depend on employment conditions, benefit levels, and other factors that affect the use of welfare. We review the econometric issues involved in analyzing monthly aggregate county-level data, and we propose a times-series cross-sectional model for explaining accessions and terminations that includes lagged dependent variables, current and lagged values of independent variables such as employment and births, and corrections for heteroscedasticity and auto-correlation. We apply this model to show that a substantial amount of the variation in accessions and terminations can be explained by the ups and downs of employment.

We then turn to individual-level data on welfare terminations, and we employ a discrete choice event history model to calculate the likelihood of exiting welfare. Once again, we show that employment changes explain differences in welfare dynamics across the county types.

We use these models to explain the higher levels of welfare receipt and quicker entry and exit from welfare for families in agricultural and rural counties compared to urban counties. We conclude with a brief discussion of the next steps for our research.

Background and Literature Review

It has long been known that a primary route onto and off welfare is a change in the employment status of the head of the household, but most of the welfare literature has neglected the role of local labor markets because of the difficulty of linking information about local labor conditions to welfare entrances and exits. Hoynes (1996) notes that studies using survey data have focused more on supply-side factors, such as education and benefit levels, than demand-side factors such as labor market conditions (e.g., unemployment rate, wage level). Studies that have included labor market variables have typically only used state-level economic conditions such as the unemployment rate, partly because of confidentiality restrictions that limit the information about the location of welfare recipients on most surveys. These studies have often found that labor market conditions have little or no impact on individual entrances and exits from welfare. But state-level economic conditions are probably too highly aggregated to capture an individual's employment opportunities. The few studies that use labor market conditions at the county or county-group level obtain mixed results. Since these studies (Fitzgerald 1995, Harris 1993, Sanders 1992) rely mainly on variation in economic conditions across areas to identify labor market effects because of the limited time span covered by most surveys, estimates will be biased if area characteristics associated with labor market conditions are excluded from the model, such as lower-skilled workers living in areas with poorer labor markets.

Using a relatively new, rich individual-level administrative data set, "Statewide Longitudinal Database—Cases," Hoynes (1996) addresses many flaws of the earlier studies, finding that local economic conditions have a significant impact on welfare exits. With six years of monthly data (1987-92) on about 100,000 welfare cases in California, she is able to estimate a discrete time hazard model in which the hazard rate (monthly exit probability) is a function of demographic, neighborhood, and quarterly county labor market characteristics, along with fixed time and county effects. Her results show that higher unemployment rates, lower employment growth, lower employment to population ratios, and lower wage growth have a significant negative impact on exit probability, leading to longer welfare spells. All labor market measures are robust to including fixed time effects except unemployment rates. Hoynes also finds that African-Americans, residents of urban areas, and two-parent households are more responsive to changes in labor market conditions, whereas teen parents and refugee groups are less responsive.

Hoynes' results provide strong support for the notion that employment conditions affect welfare participation decisions at the micro-level of individuals or households. Additional support is provided by a related literature on welfare caseload trends at the aggregate or macro-level. In two recent papers using state panel data to model caseload dynamics, economic growth was identified as the major contributor to caseload decline from 1993 to 1996 (U.S. Council of Economic Advisers, 1997; Ziliak et al., 1997).[4] Blank's caseload model (1997), which uses annual state-level panel data and is more fully specified than many other models, suggests that the state unemployment rate has a significant positive effect on both the one-parent caseload (formerly called AFDC-Basic) and two-parent caseload (formerly called AFDC-Unemployed

Parent).[5] Blank also concludes that caseloads are responsive to economic conditions by using vector autoregression with monthly data on state caseloads and unemployment rates.

Rather than focusing just on the aggregate caseload, a few studies model the two flows that comprise changes in the caseload level: accessions or new case openings, and terminations or case closings (Albert [1988] for California; Bluestone and Sumrall [1977] for New York City and upstate New York, Georgia, North Carolina, and Washington; Brady and Wiseman [1998] for California; Congressional Budget Office [1993, Appendix B] for the nation). Considering the components separately is important because their determinants are likely to differ, and thus have different policy implications. The most comprehensive model of this type is by Peter Brady and Michael Wiseman for California over the time period 1972 to 1996. This model is the starting place for our aggregate county-level model.

In the Brady and Wiseman model, which uses monthly data, the dependent variables—accession and termination rates—are hypothesized to be a linear function of demographic, economic, and policy factors.[6] The economic variables appear to have a much larger influence on two-parent cases than one-parent cases. In the equations for one-parent cases, the only economic effect that is statistically-significant is the negative impact of female potential earnings on accessions. For both accessions and terminations for two-parent cases, the unemployment rate has a significant effect with the expected sign. The other significant economic effects for two-parent cases are the negative effect of both employment growth and minimum wage on accessions, and the unexpected negative effect of female potential earnings on terminations.

These aggregate caseload studies provide strong evidence for the importance of economic variables for welfare dynamics, but they typically involve such large geographic areas (entire states) and such aggregate data (monthly or annual caseloads) that the nuances of local labor markets, especially the differences among urban, agricultural, and rural labor markets, are obscured.

Some literature on rural and agricultural areas addresses issues regarding the link between employment and welfare (or more often, poverty) in rural and agricultural counties. Most of these studies use a broad urban-rural dichotomy to classify areas.[7] Duncan and Sweet (1992) state that rural areas are characterized by higher levels of poverty than urban areas, and rural poverty reflects the limited opportunity structure in these areas, since available work "tends to be low-paying and volatile—part-time, seasonal, and subject to booms and busts in national and international markets." Using 1980 Census data, Tickamyer (1992) examines variation among 29 rural labor markets in Kentucky, North Carolina, Tennessee, Virginia, and West Virginia.[8] She finds that workers in diversified rural labor markets do better than those in narrow, resource-based labor markets, such as agriculture and mining. Her analysis also finds that rural labor markets have more working poor (employed people whose incomes are too low for them to leave poverty) than urban areas. Focusing specifically on agricultural areas in California, Taylor, Martin, and Fix (1997) find support for their hypothesis that farm employment, largely through its demand for immigrant labor, has a significant positive effect on poverty levels in these areas, which in turn affects welfare demand.[9] Since they use 1990 Census data to estimate their model, they are unable to model dynamics across time.[10]

By using monthly county-level data on accessions and terminations and individual-level data on terminations, our study provides much greater detail over time about the impact of local labor markets on welfare participation in counties with different kinds of economies.

Descriptive Data on Counties

County Typology

There are many useful ways to classify counties, but we focus on economic and demographic characteristics because there are good reasons to believe they are especially important for the dynamics of welfare. To develop a meaningful typology, we collected data on about ten economic and demographic characteristics of counties, such as percent rural population, population density, unemployment rates, and percent farm and agricultural services employment. We then used factor analysis, cluster analysis, and other data reduction techniques to recognize groups of counties with similar characteristics.

A useful classification scheme follows from the clusters produced when we place each county on a plot of percent rural by percent farm and agricultural services employment.[11] Four clusters of counties appear when this is done (see Figure 1). The fifteen counties with more than 11.5 percent agricultural employment (to the right of the vertical dashed line on Figure 1) can be considered “agricultural.” They are, not surprisingly, predominantly in California’s Central Valley with five in the Sacramento Valley and six in the San Joaquin Valley. Two others are in the Salinas Valley, and the remaining two are at the opposite ends of the state — the far northeast corner and the far southeast corner.

Counties with less than 11.5 percent agricultural employment fit into three categories depending on their level of urbanization. Those counties with more than 50 percent rural population (above the horizontal dashed line on Figure 1) and less than 11.5 percent agricultural workers are called “rural.” These seventeen rural counties are primarily in the mountainous northern and eastern parts of the state or along the northern coast. The remaining counties are less than 50 percent rural and have low levels of farm and agricultural workers. They fall into two groups. The twelve counties in the lower left-hand corner of Figure 1 are all highly urbanized with very little farming. These “urban” counties include four southern counties (San Diego, Orange, Los Angeles, and San Bernardino), seven San Francisco Bay Area counties (San Francisco, San Mateo, Santa Clara, Alameda, Contra Costa, Solano, and Marin) and one Central Valley county (Sacramento). Our residual category, “mixed,” consists of the final fourteen counties. Most of these counties have between five and 11.5 percent agricultural employment and less than about 20 percent rural population. The geographic distribution of the county types can be seen in Figure 2.[12]

The twelve urban counties comprise about 72.7 percent of the population and 70.7 percent of the welfare caseload in California. The seventeen rural counties are 2.1 percent of the population and 1.8 percent of the welfare caseload. The fourteen mixed counties comprise about 16.5 percent of population and 14.7 percent of welfare cases. The fifteen agricultural counties are 8.8 percent of the population and 12.8 percent of the caseload. Thus, the agricultural counties have a disproportionate share of the welfare population in California.

Other typologies are possible, but our experience with the welfare and employment data suggests that the typology we use captures some important differences across counties. For this reason, we will use it throughout this paper as a way to distinguish county types.[13]

Differences Across Counties in Welfare and Employment Dynamics

Agricultural counties in California have a higher average welfare population and more annual variation in that population than all other kinds of counties.[14] Urban counties have the lowest welfare population as a fraction of the total population (5.2 percent) and the lowest yearly variation in the ratio of welfare participants to total population as shown in figures 3 and 4.[15] Mixed and rural counties are in-between on both measures. Agricultural counties have the highest percent on aid (9.6 percent) and the greatest variability in the percent on aid.[16]

A great deal of the variability in the nonurban welfare caseload comes from significant seasonality in the caseload. This seasonality is most apparent by considering the dynamics of accessions to welfare (the number of cases entering in a given month) and terminations (the number of cases leaving in a given month). Figure 5 plots the average rate of accessions and terminations per 1000 people in agricultural counties for two-parent or unemployed parent (U) cases by month of the year over the time period of our data (1985-1997).[17] The vertical axis is the number of cases entering or exiting welfare per 1000 people in agricultural counties. There is an obvious upsurge in terminations during the summer months (roughly May to October) and a down-surge in accessions at the same time.

The net effect of this seasonal variability is a drop in the caseload in agricultural counties over the summer and an increase during the winter. Figure 6 shows that there is a similar seasonality in rural and mixed counties but not in urban counties. This figure plots the average of accessions minus terminations divided by population (in thousands) for U cases by month of the year and by county type. Thus the vertical axis is the net number of new cases per thousand population. This figure clearly shows the much greater seasonal variability in nonurban versus urban counties. The line for urban counties is almost flat (ranging from zero to .05) while the line for agricultural counties goes from -.20 to .35. Rural counties are almost as variable as agricultural counties, and mixed counties are, as we might expect, in-between urban counties and agricultural/rural counties.

Figures 7 and 8 are the same plots for FG (family group), one-parent cases (usually a single mother). With only one parent available to work, there has always been much less workforce participation in the FG cases than the U cases, so we would expect them to be much less sensitive to employment conditions. Figure 7 depicts the monthly changes in accessions minus terminations divided by population in thousands for agricultural and urban counties. As we would expect, the variation in these series is less than what we found for the U cases, but the pattern is similar. Although there is a substantial amount of variability for urban counties, it does not seem to be seasonal, whereas the variability for agricultural counties is clearly seasonal. Figure 8 reveals seasonality for both mixed and rural counties, but it is greater for rural counties.

These differences appear to be related to the seasonality of employment. The earlier figures 3 and 4 include unemployment rates and the variability in the unemployment rate next to the data on welfare populations. These figures reveal an obvious and strong relationship between unemployment and welfare caseloads, and a strong relationship between variability in unemployment over the course of a year and variability in those on aid.

To investigate the role of employment variability over the course of a year, Figure 9 plots mean farm employment divided by civilian labor force by county type over the twelve months of the year. The differences in levels for farm employment result from the method used to classify the counties. The substantial seasonality in farm employment evident in this figure could go a long way towards explaining some of the variability in welfare caseloads for agricultural and mixed counties, but it seems unlikely that it could play much of a role for rural counties because of its low level and much smaller variability in rural counties.

We must look elsewhere for an explanation for the variability in rural counties. Figures 10 and 11 consider two other components of the employment series. Figure 10 plots retail employment[18] and Figure 11 plots all "other" employment that is not agricultural, retail, or service. These figures suggest that retail and “other” employment might be the source of variability in welfare caseloads in rural areas, but these series would do little to explain variability in other counties. A close comparison of Figure 10 for retail employment with figures 9 and 11 for farm and other employment indicates, however, that the variability in retail employment in rural counties is not that great compared to the variability in farm employment in agricultural counties or the variability in other employment in rural counties. Retail employment in rural counties ranges from about 12.5 percent of the civilian labor force in the winter to about 13.5 percent in the summer; farm employment in agricultural counties ranges from about 12.5 percent to almost 20 percent and other employment in rural counties ranges from about 52 percent to 58 percent. Clearly, some of the components of other employment are important for rural economies. Our hope had been to decompose the “other” employment into its components to search for the exact cause of rural variability, but we are still trying to solve the difficult problems of piecing together monthly employment series in cases where some are censored to preserve confidentiality.

These figures strongly suggest an association between employment and welfare caseloads. In the remainder of this paper we pin this down more formally. In order to facilitate this task, we begin by developing a model for welfare accessions and terminations.

Development of the Model and Econometric Issues

Theoretical Model

In the following, we derive a model of welfare accessions and terminations for aggregate data from an individual-level model. This model is used as the basis for the aggregate analysis of accessions and terminations, and the micro-level analysis of terminations.

Accessions— For accessions to welfare, assume there are k different mutually exclusive and exhaustive groups that are "at-risk" for moving to welfare and each group has a different susceptibility of entering welfare. In the limit, of course, each group k could be a different person. Represent the number of people in each at-risk group as "R_{itk}" where i stands for individual county, t stands for time, and k stands for the kind of subgroup such as "women between age 15-44 who just gave birth to children in county i at time t". Because the groups are mutually exclusive and exhaustive, the total number of at-risk people is:

(1) $$R_{it} = \Sigma_{\mathrm{k}} \; R_{itk}$$

where Σ_k is the summation over the k groups. Splitting the population up this way is nothing more than an accounting convention. The power of doing so comes from assuming that the probability of an accession is the same for each person within a group but perhaps different across groups. Hence we assume:

(2) b_{itk} = Probability of accession for a person in group k in county i during month t.

More general assumptions are possible,[19] but this one is a good starting place.
Part of the art of developing a model for aggregate data is choosing the right set of k groups given the available data. If the entire population is initially considered at-risk, then some subgroups (e.g., the elderly) will have nearly a zero chance of getting on welfare. Indeed, at least one group,

those already on welfare, will obviously have a zero chance of getting on welfare during the current period. It seems reasonable to exclude these people from our at-risk group.[20] We have chosen to ignore all groups other than women age 15-44 who are not now currently on welfare, and we have broken this group into two parts: those within this group who just gave birth in the last year and those who did not.

We could also assume that individual accessions are independent of one another so that the total number A_{itk} is a binomially distributed random variable with expectation equal to $b_{itk} R_{itk}$ and variance equal to $(b_{itk}(1 - b_{itk}))/R_{itk}$. Then we could write the total number of accessions as follows:

$$A_{itk} = b_{itk} R_{itk} + \varepsilon_{itk}. \tag{3}$$

where the error ε_{itk} has mean zero and variance $(b_{itk}(1 - b_{itk}))/R_{itk}$. Note that this variance becomes smaller for larger counties or groups. Equation (3) holds even if individual accessions within a county are dependent on one another, and as long as the dependence is not too great, the variance of ε_{itk} will decline with county size.

For some kinds of groups (FG and U) we can observe the number of accessions for each group. In that case, we can estimate equation (3) if we make some assumption about the b_{itk} such as constancy over all time periods and counties ($b_{itk} = b_k$). For other groups (women age 15-44 who are not currently on welfare and who just had a child) we do not have information about accessions from each kind of group. Rather, we observe the total number of accessions that results from summing (3) over the k groups to get the aggregate quantity A_{it}. Before we undertake this summation, it is useful to write each R_{itk} as follows:

(4) $$R_{itk} \;=\; d_{itk}\, R_{it},$$

where $d_{itk} = R_{itk}/R_{it}$ which is the share of the at-risk population in group k in county i at time t. Obviously d_{itk} just defines the group's "share" of the total at-risk population.

With this notation, we can write the accessions equation (3) as follows:

(5) $$A_{itk} \;=\; b_{itk}\, d_{itk}\, R_{it} + \varepsilon_{itk}$$

And total accessions is the sum across all groups k:

(6) $$A_{it} \;=\; \Sigma_k\, A_{itk} \;=\; \Sigma_k\, (b_{itk}\, d_{itk}\, R_{it}) \;+\; \Sigma_k\, \varepsilon_{itk} \;=\; R_{it}\;\; \Sigma_k\, (b_{itk}\, d_{itk}) \;+\; \Sigma_k\, \varepsilon_{itk}.$$

We divide both sides by R_{it}:

(7) $$A_{it}/R_{it} \;=\; \Sigma_k\, (b_{itk}\, d_{itk}) \;+\; (\Sigma_k\, \varepsilon_{itk})/R_{it}.$$

The left-hand side can be computed because both quantities—total accessions and total at-risk people—are known. Moreover, for many groupings of the at-risk population we might very well have information on the d_{itk}, the shares of each kind of at-risk population. Consequently, if we make some assumption about the b_{itk} (such as as constancy over all time periods and counties, $b_{itk} = b_k$), then we can regress A_{it}/R_{it} on d_{itk} to get estimates of the b_k, the probability of entering welfare for people in group k.

More generally, we assume that the probabilities b_{itk} can be written as county fixed effects (c_i), period fixed effects (e_t), effects resulting from independent variables that may vary by time, county, and group (the vector X_{itk} and the vector of coefficients g_k), and a quantity ψ_{itk} representing all omitted variables that might explain variation in the probabilities of getting on welfare:

$$(8) \qquad b_{itk} = c_i + e_t + X_{itk}\, g_k + \psi_{itk}.$$

We assume that the residual ψ_{itk} has zero mean, is independent of the c_i, e_t, X_{itk} and d_{itk}, and has variance σ_k^2.

The assumption of independence is a strong one, but it would be hard to get much farther without making it. Other assumptions about the variance are possible, but it seems most reasonable to assume that it depends on the group k and nothing else. The X_{itk} variables could be unemployment rates, program benefits, time on welfare for the group, or any other relevant characteristics.[21] If we had individual level data (that is, if each k were an individual instead of a group), then we could estimate (8) directly as a linear probability model by using whether or not the individual went on to welfare at time t as the dependent variable. Alternatively, we could use another version of the discrete choice model such as the logit or probit. We choose the linear probability model in this case primarily because it leads to a much simpler model for aggregate data. But the linear probability model can also be justified on the grounds that we get very similar results with probit and the linear probability model when we analyze individual-level data later in the paper.

Substituting (8) into (7) we immediately see the advantage of the linear form as we get:

$$(9) \qquad A_{it}/R_{it} = \Sigma_k (c_i + e_t + X_{itk}\, g_k + \psi_{itk})\, d_{itk} + (\Sigma_k\, \varepsilon_{itk})/R_{it}$$

$$= c_i + e_t + \Sigma_k (X_{itk}\, g_k) d_{itk} + [\Sigma_k (\psi_{itk}\, d_{itk}) + (\Sigma_k\, \varepsilon_{itk})/R_{it}].$$

Note that this equation includes interactions of the fractions of each at-risk population d_{itk} with the X variables. One of the X variables can be assumed to be a constant, and a minimal specification would include just this constant (with no other X variables and no c_i or e_t) so that the equation reduces to just the shares d_{itk} multiplied by the g_k. In this case, the expected total accession rate will be the weighted average (with the shares of each group d_{itk} as the weights) of the expected probability of an accession g_k from each group k.

The error terms in (9) will be uncorrelated with the explanatory variables c_i, e_t, X_{itk} and d_{itk} given the assumptions of independence above.[22] Consequently, equation (9) can be estimated using standard regression methods, but some attention must be given to the form of the error term which is extremely heteroscedastic because of the second term. The first error term has a variance of $\Sigma_k\, d_{itk}^2\, \sigma_k^2$ which might be roughly equal across counties and time if the d_{itk} and σ_k^2 do not vary too much. The second error term, however, has a variance, in the case of independence across observations, of $[\Sigma_k\, b_{itk}(1 - b_{itk})/(R_{itk}\, R_{it}^2)]$ which can be written as $[\Sigma_k\, b_{itk}(1 - b_{itk})/d_{itk}]/R_{it}^3$ This variance decreases with the cube of the at-risk population in a county, and it should be roughly constant within a county over time because the at-risk population would typically not change very much. These results suggest that any estimation of (9) must take into account substantial heteroscedasticity across counties.

Terminations— The model for terminations is very similar except that the at-risk group is the current caseload and there is no way to break terminations into separate groups (except FG and U). Thus, we drop the subscript *k* and write:

$$(10) \qquad T_{it}/L_{it} \;=\; c_i + e_t + X_{it}\,g \;+\; \psi_{it} \;+\; \varepsilon_{it}/L_{it},$$

where L_{it} is the current caseload. This equation presents the same kinds of estimation problems as (9) above.

Independent Variables and Specification— This model allows substantial flexibility in specification, and this section considers what can be done. Assume two different at-risk groups:

— Women between age 15-44 who just had a birth (k=0 so that we have R_{it0} of them).

— Women between age 15-44 who did not just have a birth ($k=1$ and R_{it1} of them).

The chances of getting on welfare are b_{it0} and b_{it1} for each group. For the sake of exposition, assume one independent variable and a constant in (8) in addition to the county and time fixed effects:

$$(11) \qquad b_{itk} = c_i + e_t + a_k + X_{itk}g_k + \psi_{itk}.$$

where c_i is a county fixed effect, e_t is a time fixed effect, a_k is a constant for each group, X_{itk} is an independent explanatory variable, and g_k is its effects. Identification requires setting one of the c_i and one of the e_t to zero, and we assume that this is done. We can write the entire model as follows by substituting (11) into (7):

$$(12) \quad A_{it}/R_{it} = c_i + e_t + \Sigma_k [a_k d_{itk} + X_{itk} g_k d_{itk}] + \eta_{it}$$

$$= c_i + e_t + a_0 d_{ito} + a_1 d_{it1} + X_{ito} g_o d_{ito} + X_{it1} g_1 d_{it1} + \eta_{it}$$

where we are ignoring the complexities of the error term by including ψ_{itk} and ε_{it} in η_{it}. Because $(d_{ito} + d_{it1} = 1)$, we must drop one of the terms with d_{itk} for identification[23] and write this as:

$$(13) \quad A_{it}/R_{it} = c_i + e_t + a_0 d_{ito} + g_o X_{ito} d_{ito} + g_1 X_{it1} d_{it1} + \eta_{it}.$$

The effect of including the k groups is to get interaction terms with coefficients a_k and g_k.

An alternative way to incorporate the impact of a group is to simply add another independent variable such as d_{ito} while dropping the distinction between groups so that we only include X_{it}. This approach produces the following specification:

$$(14) \quad A_{it}/R_{it} = c_i + e_t + a_0 d_{ito} + g X_{it} + \eta_{it}$$

This comparison makes clear the implications of accounting for group differences by including an independent variable such as d_{ito} for the group in (14) versus specifying different accession probabilities b_{itk} for each group which leads to the additional term in (13). In fact, we can compare (13) and (14) directly if we assume that X_{it} is the weighted average of X_{ito} and X_{it1}:

$$(15) \qquad X_{it} = X_{ito}\, d_{ito} + X_{it1}\, d_{it1}$$

Solving for X_{it1} and substituting in (13) produces the following:

$$(16) \qquad A_{it}/R_{it} = c_i + e_t + a_0\, d_{ito} + g_1\, X_{it} + (g_0 - g_1)\, X_{it0}\, d_{it0} + \eta_{it},$$

which shows clearly that the difference between (13) and (14) is the additional interaction term $(g_0 - g_1)\, X_{it0}\, d_{it0}$. Note that this interaction term will remain even if $X_{ito} = X_{it1}$

These differences stem from familiar differences in individual-level specification. Equation (14) comes from allowing for group differences by employing a dummy variable for membership in the group in a version of equation (8) with the k subscript dropped. Equation (16) comes from accounting for group differences by allowing for completely different accession probabilities for each group in (8) by having regression coefficients that vary by k. In effect, this amounts to interacting the dummy variable with all terms in the equation (except the county and time dummy variables). These familiar individual-level differences lead to aggregate specifications in which each group's proportion in the population, $d_{itk,}$ replaces the dummy variables.

An example illustrates these points. If $X_{ito} = X_{it1} = X_{it}$ as would be true for unemployment or benefit levels in equations (14) and (16), then we would expect that g_1 would be positive because higher unemployment would lead to more accessions. If group $k = 0$ is women between the ages of 15-44 who had children in the last year and group $k = 1$ is all other women between the ages of 15-44, then we might also expect a_0 to be positive because more of the first group would increase accessions. In addition, we might also expect an interaction between unemployment and the group of women who recently had children. Thus (16) would be a better specification than (14), and we might expect that $(g_0 - g_1)$ will be positive because those women who recently had children will be more adversely affected by high unemployment than those women who did not. Thus an increase in births and an increase in the unemployment rate will cause an increase in accessions because of the difficulty of those families getting jobs in a weak labor market.

Econometric Issues

Equation (9) raises a host of econometric issues. To simplify our discussion we write $Y_{it} = A_{it}/R_{it}$, $Z_{it}\, h = \Sigma_k\, (X_{itk}\, g_k) d_{itk}$, and $\eta_{it} = [\Sigma_k\, \psi_{itk}\, d_{itk} + (\Sigma_k\, \varepsilon_{itk})/R_{it}]$. Then we consider:

$$(17) \qquad Y_{it} = c_i + e_t + Z_{it}\, h + \eta_{it}.$$

With time-series cross-sectional data, there are substantial reasons to worry about heteroscedasticity, spatial auto-correlation, temporal auto-correlation, and lagged values of the independent and dependent variables.

Heteroscedasticity can often result from a failure to include unit fixed effects, but we have included county fixed effects in this model. But the vastly different at-risk populations in the counties are another reason to expect heteroscedasticity in η_{it}. In California, the populations of counties range from Alpine and Sierra with about 1,000 and 3,300 residents respectively to Los

Angeles with almost ten million people. We have corrected for this problem in two different ways in our statistical work. One approach is to assume that almost all of the heteroscedasticity is across counties (and not across months within counties) so that the variance of η_{it} is σ_i^2 which varies across counties but not over time. A second approach is to use weighted least squares where the weight depends on some power of the populations of the counties.[24] We find that the results from the two approaches do not differ very much so we have only reported the results from the first method.

Spatial auto-correlation can result when similar forces, such as economic upturns or downturns, affect counties that are located near one another. In the future, we hope to consider such contemporaneous (or lagged) correlation across counties, but we have ignored it in the current paper.

With time series data, it seems likely that welfare accessions and terminations depend on lagged values of the independent variables, especially employment. We have experimented extensively with different lag lengths, and have found that five lags suffice to capture the dynamics of employment.

With monthly data, it also seems quite likely that there will be temporal auto-correlation even after we account for the seasonality in the data. Indeed, we find evidence for an auto-regressive process with an auto-correlation of about .40 for all our dependent variables. One way to deal with this is to make corrections for an AR(1) or higher order process. Another approach is to include lagged dependent variables on the right-hand side of (17) in order to "whiten" the error term. With short panels and a fixed number of time periods, lagged dependent variables in fixed effects models lead to inconsistent parameter estimates (see Hsiao, 1986; Baltagi, 1995; Beck & Katz, 1995), but with the long panels that we have, these problems can be ignored. We find that including about four lagged values of the dependent variable in our specifications reduce the AR(1) parameter for the error term to insignificance or near-insignificance suggesting that the error term is white noise once these lags have been included.

Aggregate Results

Data and Specification

The Data— The dependent variables for our aggregate data analysis come from the California Department of Social Services series, *Public Welfare in California*, which provide monthly information by county on the number of cases, terminations and accessions for both the unemployed parent (U) program and the family group (FG) program from July 1985 to August 1997 (146 months). We drop three small counties, Alpine, Sutter, and Yuba, from our analysis because of data problems.[25] If all data were available for the remaining 55 of the 58 California counties for this time period, we would have 8,030 observations. Because we are missing the first eighteen months of employment data for eleven counties,[26] we lose 198 observations. Finally, because we lag the employment data up to five periods, we lose an additional 275 (55 X 5) observations, leaving us with 7,557 observations. All of the aggregate specifications in this paper include this number of observations.

The "at-risk" groups for accessions (ignoring the adjustment we make for those already on welfare) are women age 15-44 who had children in the last year and women age 15-44 who did not have children in the last year.[27] We obtained these data from the California Department of Finance web site.[28] These numbers were adjusted by subtracting off the number of women on welfare.[29] The "at-risk" groups for terminations are the total caseload in the preceding month in the unemployed parent program for U-terminations and the total caseload in the preceding month in the family group program for FG-terminations.

The employment data come from the Labor Market Information Division (LMID) of the California Employment Development Department web site.[30] We use both labor force data which reflect the employment status of individuals by place of residence and industry data which reflect jobs by place of work.[31] We use monthly data series by county for farm employment, retail employment, service employment, and total employment to construct a series for all nonfarm, nonretail, and nonservice employment. We call this series "other" employment. We used civilian labor force as the denominator and farm, retail, service, or other employment as the numerator to get the fraction of farm, retail, service, and other employment. The residual category was the unemployment rate. The fractions of farm, retail, service, and other employment and the unemployment rate necessarily sum to one. Hence, one of them (always the unemployment rate in our models) was omitted from our regressions.

County and time dummy variables were included in all regressions, but their values are not reported. The inclusion of time dummy variables provided controls for changes in program benefits, policy changes, and other changes that were national or statewide.

The Specification— The econometric specification followed the logic described in Section III. The primary dependent variables were accession rates to the U program, accession rates to the FG program, termination rates from the U program, and termination rates from the FG program.

Each model included county specific and time fixed effects. The county fixed effects pick up mean differences across counties in accessions or terminations, and the month-year fixed effects pick up mean differences from month to month in accessions or terminations.

Since our major goal was to identify and explain seasonal welfare cycles, we also included in the specification three interaction terms of type of county (agricultural, rural, or mixed) times summer months defined as May to October. The baseline category is urban counties during summer months, and the seasonality in urban counties (which appears to be slight) serves as the baseline for interpreting the interaction terms. In models with just county and time fixed effects, these interaction terms pick up the increase in terminations or the decrease in accessions that occurs (beyond the baseline) during the summer months compared to the winter months in agricultural, rural, or mixed counties.

If seasonal welfare cycles are more pronounced in agricultural, rural, and mixed counties than in urban counties, then the coefficients of these interaction terms should be large and highly significant. In addition, if employment variables explain seasonal welfare cycles, then we expect the coefficients of these county type times summer interactions to diminish substantially as the employment variables are added to the models. Thus, our analysis strategy goes beyond looking for significant coefficients on the employment variables. We will also look for a substantial diminution in the size of the coefficients on the county type by summer months interaction terms.

Heteroscedasticity, Auto-Correlation, Lagged Dependent Variables and Lag Lengths— Before settling on a standard specification, we experimented with a number of ways to deal with heteroscedasticity and temporal auto-correlation. As noted earlier, allowing for county specific error variances eliminated heteroscedasticity.[32]

In specifications without lagged dependent variables (LDVs), there was substantial auto-correlation in the residuals, and the auto-regressive parameter varied from around .397 to .446 across different dependent variables and differences in specification. With the addition of four

LDVs, the auto-regressive parameter dropped to between .026 and .152, the coefficients on the LDVs were highly significant and declining as we would expect (see Table 1), and the log-likelihoods increased very substantially. Moreover, once the LDVs are added to the models, it does not appear that a correction for auto-correlation in the errors is necessary. Estimates of the models with LDVs with just a correction for heteroscedasticity have the same likelihoods as estimates of the same models with a correction for heteroscedasticity and for common auto-correlation. Thus, if we include LDVs, we only need to correct for heteroscedasticity and not common auto-correlation because the errors have been sufficiently "whitened."[33]

Another specification decision involved determining the lag lengths for the employment variables. We tried specifications with the current value and up to eleven lags (to cover the entire length of a year). We found that five lags on the employment variables are sufficient to capture all the dynamics in welfare accessions and terminations.[34]

Substantive Results and Implications

Substantive Results— Table 1 presents the results of two different specifications for four different dependent variables which are U and FG termination rates and U and FG accession rates. Each specification has county and time fixed effects, and a correction for county heteroscedasticity. The top of the page reports estimates for these four dependent variables for models that include LDVs, current and lagged employment variables, the fraction of the at-risk population giving birth in the past year,[35] and the county type by summer interactions. To simplify the table, only three of the five lags on the employment variables are reported and nothing much is lost by doing this. The bottom of the page reports the county type by summer interactions for models with only these interactions and LDVs (whose coefficients are not reported). The four models at the bottom of the page measure the amount of seasonality (over and above that in the baseline urban counties) of accessions and terminations in agricultural, rural, and mixed counties.

The county type by summer interactions can be compared across the two specifications. We would expect them to be positive for terminations and negative for accessions. If labor market conditions explain the seasonality in nonurban counties, then we would expect the coefficients for these interactions in the full model with employment and other variables to be much smaller in absolute value than those for the models at the bottom of the table which include only LDVs and the interactions. Ideally, the interactions would fade into insignificance in the full specification. Although they do not become insignificant, they do become smaller for the first three columns. For example, the agricultural county times summer interaction for U terminations declines from .012 in the specification without employment variables to .006 in the full specification. The same interaction for U accessions goes from -.0004 to -.0002.

We would also expect that the impact of labor market conditions would be larger for U cases than for FG cases because single mothers in FG cases typically work much less than the head of the household in two-parent U cases. The impacts of the full specification on the county type by summer interactions are much smaller for FG terminations, and they are very odd for FG accessions where the coefficients of the interaction terms are unaccountably *positive* meaning that there are *more* FG accessions in the summer months in these counties. We shall return to this anomaly.

Now consider the impact of the employment variables on the models at the top of the page. We would expect that the impacts of employment, especially contemporaneous employment, would be positive for terminations and negative for accessions and that they would be larger for U cases than for FG cases for the reasons described above. We might also expect that the coefficients on the lagged employment variables would vary in sign because of the presence of the lagged dependent variables and the relatively complicated dynamics of the relationship of employment to welfare accessions and terminations.

The coefficients on the contemporaneous employment variables, especially for farm, retail, and other employment, are almost always of the right sign (positive for terminations and negative for accessions) and statistically significant. The one exception is the FG accessions equation for which the signs are mostly wrong and mostly insignificant. In all the specifications, the lagged values of the employment variables are typically negative, and it is difficult to interpret them in this set-up because of the inclusion of the lagged dependent variables.

The standard way to determine the equilibrium impact of a long-term change in a variable such as farm employment is to sum the coefficients of lags. But we cannot do this here because we must also take into account the impacts that are funneled through the lagged dependent variables. Thus, for example, a ten percent increase in farm employment will have an immediate -.00075 impact on U accessions, which is the product of the coefficient on contemporaneous farm employment (-.0075) times the size of the change in farm employment (.10). In the next period it will continue to have this impact, but it will also have an impact through farm employment lagged one period (the coefficient of -.0038 times the change of .10) *and* an impact through the lagged dependent variable (which will be the product of three terms: the coefficient of the LDV which is .3042, the contemporaneous impact of farm employment which is -.0075, and the size of the change in employment which is .10). The net result will be an impact of:

$$(-.0075 \text{ X } .10) + (-.0038 \text{ X } .10) + (.3042 \text{ X } -.0075 \text{ X } .10) = -.00136.$$

The calculation of the ultimate equilibrium effect requires going forward enough periods until the additional terms become negligible.

These calculations are tedious, and it is much easier to take another approach. Table 2 presents the results for models that are identical to those in Table 1 *except* that the lagged dependent variables have been dropped. These models are also estimated in the same way with no correction for auto-correlation. As a result, there is substantial residual auto-correlation, but we know that the estimates of the coefficients are statistically consistent — only the standard errors are suspect because of the failure of the standard sphericality assumption.[36] The virtue of these results is that we can now sum the coefficients of the employment variables to determine equilibrium impacts. Note that the sum of the first two coefficients of the farm employment variables for U accessions is -.0141. The product of this sum and the size of the change in employment (.10) is -.00141, which is within rounding error of the calculation performed above. We would expect this result if the two specifications are capturing the same dynamics.

Table 2 shows that the impact of employment on terminations is mostly immediate whereas current and last month's employment both have an impact on accessions. It makes sense that terminations may be affected immediately because someone who gets a job which pays enough to end their stay on welfare will be terminated immediately, whereas someone who loses a job may take a while before they seek to go on welfare.

Implications— It is instructive to calculate the size of the impacts of employment using the results from Table 2 and the data from Table 3 which lists the means and standard deviations for the dependent and independent variables by county type. For example, a standard deviation change in farm employment in agricultural counties is .078 and this would lead to an immediate impact on U terminations of (.247 X .078) = .019, where .247 is the coefficient on the contemporaneous farm employment for U terminations in Table 2. This would be an 18 percent change in U terminations from its average level of .106 in agricultural counties. The standard deviation of .078, however, may be a poor standard for thinking about realistic changes in employment because it conflates time-series and cross-sectional variation in farm employment. A better measure would be the typical variability of farm employment within a county over the course of a year which is about four percent. This figure still leads to a nine percent change in U terminations. Turning to U cases, the impact of a four percent change in agricultural employment on U accessions in agricultural counties would be (-.0077 X .04)/.003736 or about an eight percent decline.

Another way to describe the impact of change is to calculate an elasticity. The elasticity of interest is the ratio of the change in farm employment divided by the level of farm employment to the change in accessions or termination divided by their level. The elasticity of U terminations with respect to farm employment in agricultural counties is about .14 so that a one percent change in farm employment leads to about a .14 percent increase in U terminations in agricultural counties. The elasticity for U accessions with respect to farm employment in agricultural counties is about minus .13.

These kinds of changes in agricultural employment have implications for the caseloads, especially the unemployed parent caseloads, in agricultural counties. Accessions and terminations to the unemployed parent program each average about ten percent of the total U caseload. A sustained eight percent change in terminations and accessions for a six month period, which is approximately what we get from the typical changes in farm employment in agricultural counties, can lead to an overall decline in U caseloads of about ten percent during that period. This decline accounts for most of the average seasonal change in U caseloads of about 13 percent.

Table 2 also shows that the fraction of the at-risk population who had children in the last year has a positive effect on accessions for both U and FG cases.[37] The share of the at-risk population who give birth in the preceding year ranges (see Table 3) from 8.7 percent in agricultural counties to 6.1 percent in rural counties, with a standard deviation of about one percent across counties within each county type. Thus, a one standard deviation or an absolute one percent increase in the fraction of the population with births in the last year increases U accessions by .000265 (see table 2) which would be about a ten percent increase in the overall level of U accessions of .002512 (from Table 3). The impact on FG accessions would be about one-third this size (.000266 over .007854). To put this another way, the elasticity of a change in U accessions with respect to the fraction of at-risk women with births is .75 and the elasticity for FG accessions is .24, which are sizeable effects.

These results show clearly that farm employment can go a long way toward explaining the seasonality in welfare caseloads in agricultural counties because much of the seasonality is due to the unemployed parent caseload. The results for FG terminations also provide part of the explanation for the weaker seasonality in FG caseloads. The results for FG accessions, however, are anomalous. The best interpretation based on the evidence would be that there is no seasonality in FG accessions. The county type by summer interactions in Table 2 support this notion, but the interactions in Table 1 suggest there may be some seasonality — but it goes in the wrong direction. FG accessions appear to increase in the summer in nonurban counties. Neither table provides much evidence for the impact of labor market conditions on FG accessions.

One of the tasks that still remains is to explain the result for FG accessions. One possibility is that FG cases increase in the summer in nonurban counties because male partners are more likely to leave in the summer when employment conditions improve to seek seasonal employment outside their counties. If this is so, then we would expect to find that U cases move over to FG status during the summer in these counties. We will eventually use the LDB data described in the next section to test this hypothesis.

Individual-level Results Using Micro-level Data

Data

The primary data set for our micro-level analyses contains the individual aid history of a ten percent sample of all Medicaid-eligible persons in California from January 1987 to December 1997. This administrative data set of monthly data, “Statewide Longitudinal Database—Persons” (LDB—Persons), was created by UC DATA at the University of California, Berkeley, under contract with the California Department of Social Services. The sample includes both a ten percent sample of all persons who were Medicaid eligible at any time in 1987, and a ten percent sample of “new” persons for each subsequent year. A new person for a given year is one who has not been Medicaid eligible from 1987 to that specific year. In addition to aid codes, the data set identifies an individual’s date of birth, gender, race/ethnicity and residential location. UC DATA also released a sample of the LDB, which is a one percent sample of Medicaid-eligible persons. We use the latter data set since its size is more manageable.[38]

For our analysis we rely on the sizeable sub-sample of the LDB who received AFDC at some point during the sample period. All AFDC recipients are automatically eligible for Medicaid, so the AFDC sub-sample is representative of the AFDC population as a whole. From the information on aid history, we construct welfare spells for individuals, which will be the focus of this analysis. Due to “administrative churning” concerns, we do not consider a spell to be over unless there is a break in aid of three months or more. Left-censored spells (those which were ongoing at the beginning of the sample in 1987) are omitted from our analysis, since we do not know when such spells began. We also eliminate spells during which a person moved from one county to another. Multiple or repeat spells, which are very common among welfare recipients, are included in the analysis.

The other data used for this analysis are county employment data from our earlier aggregate-level analysis. The primary employment variables are farm, service, retail and other employment. Since the LDB data set includes residential location, we were able to merge the employment data with the individual-level data from the LDB.

Model

The LDB follows a sample of California welfare recipients throughout their welfare spells. Because it only includes those people who enter welfare, the LDB alone cannot be used to study accessions or entrances to welfare. But it can be used to study exits from welfare. In effect, the LDB has data on a sample of the population that is at-risk for leaving welfare, and it can be used to study terminations among this group.

The equation that is estimated is a variant of (8) for the case where k is an individual, t is the calendar month, i is used to identity the county in which the individual resides in order to allow the matching of employment and other data as independent variables, and a new subscript s is added to represent the month of a person’s spell:

(18) $\quad b_{itks} \;=\; c_i \;+\; e_t \;+\; X_{itks}\, g_k \;+\; \psi_{itks.}$

The index s indicates how many continuous months person k has been on welfare. There are no observations for a person who has not yet come on welfare or who has exited welfare in some earlier month. The dependent variable b_{itks} is zero if person k does not exit welfare after month s, and it is one for exit if s is the last month of a completed spell.

This approach amounts to estimating a discrete time hazard model. The hazard or exit rate b_{itks} is a conditional probability. It is the probability of person k leaving welfare in month s of his or her welfare spell conditional on the person having received welfare for $s\text{-}1$ periods and conditional on some covariates such as X_{itks} or c_i. The covariates can vary with the person, the county, with time on welfare, or with calendar time. In our model, the hazard rate is a linear function of the covariates or explanatory variables of age, county employment variables, spell duration effects, and month-of-year and county fixed effects. It is crucial to control for month of year because certain seasonal fluctuations in the welfare data are artifacts of the way Medicaid eligibility data are collected in California. We include county fixed effects to control for omitted area characteristics, since these omitted variables would lead to biased results if they are associated with employment variables.

The dummies that control for spell duration effects for the first six years are those Hoynes (1996) chose for her hazard model after extensive testing. The 29 duration dummies are for each month for the first year of a welfare spell, for three-month periods for the next two years, for six-month periods for the following three years, for one-year periods for the next two years, and finally for a three-year period for the next three years of a spell. Our analysis, along with those of many others, find that the hazard or exit rate increases during the initial months of a welfare spell, and then decreases steadily for the spell's duration.

We use a discrete-time event history model because it is easily understood and executed, allows for time-varying explanatory variables, and uses information on uncompleted or right-censored spells. For this model a separate observation is created for each month an individual receives welfare (spell-month), and standard estimation methods such as ordinary least squares (for a linear probability model) or probit can be used.

In our final sample we exclude spell-months for people under age 16 and over age 54, because employment is a less likely option for them. Since our employment series does not include data for the most recent months, a couple of counties, and a handful of months for a few counties, our sample is further reduced. Our final sample includes 468,418 spell-months for people in one-parent households and 188,357 spell-months for people in two-parent families. It covers the 125-month time period from April 1987 to August 1997.

Results

The results from the discrete-time hazard model corroborate our findings at the aggregate level. First we find support for the notion that the nonurban welfare caseload is more cyclical or variable. Indeed the average welfare recipient in either a rural or agricultural county has both more and shorter welfare spells than the average welfare recipient in an urban county. A person in an agricultural or rural county is therefore more likely than a person in an urban county to go on welfare in a given year; however, once on welfare, she is more likely to exit welfare before an urban welfare recipient who began welfare at the same time. For example, our results suggest that a rural welfare recipient is about 60 percent more likely to exit welfare in her first year on welfare than an urban welfare recipient, who is otherwise the same in every way.[39]

Next we find support for the finding that significant seasonality exists in the nonurban caseload, pertaining to a "summer effect." We find that the average welfare recipient in an agricultural or rural county is more likely than the average welfare recipient in an urban county to exit in the summer months than in the winter months. Compared to the summer and winter exit rates for an average welfare recipient in an urban area, the summer exit rate for an average rural welfare recipient is, on average, 50 percent higher than the winter rate, and for an average agricultural welfare recipient it is 25 percent higher.[40]

Employment effects— Our final results provide support for the aggregate findings on the relationship between welfare and employment dynamics in agricultural and rural counties. Table 4 summarizes the results for two separate specifications, one without employment variables and one with them, for FG and U cases. The full model includes the covariates described above (age, month-of-year, county fixed effects, and spell duration effects) in addition to county type by summer interactions and employment variables, but we focus here on the impacts of labor markets on exits from welfare. The estimations reported here are simple ordinary least squares. Probit models were also estimated, but the results did not change appreciably. The OLS estimates are presented because they are easy to interpret.

Note that the interactions all have the right (positive) sign in the specifications without employment variables, although they are only large and significant for unemployed parent or U cases. When employment variables are added to the specifications, the coefficients of the interactions are reduced in size and become less significant. Furthermore, the coefficients on farm and other employment are very large and significant. The coefficient for retail employment is significant for two-parent U cases but not for FG cases. The coefficient for service employment is large and significant for FG but not U cases. These results are roughly the same as we found before, but the results for retail and service employment are somewhat different.

Next Steps

We believe our analysis to date shows that employment dynamics drive differences in welfare-use patterns among county types. At the same time, we want to take a number of additional steps to make our current results even more definitive. We also want to use the models we have established in this paper to continue to explore some issues we have already raised, and begin to explore related issues.

Among our immediate next steps, we want to examine the exact cause of the variability in the rural welfare caseload by decomposing the "other" employment category into its components. To do this, we still need to solve the difficult problems of piecing together monthly employment series in cases where some are censored to preserve confidentiality. We also intend to improve the specification of our model by adding more covariates. For example, we plan to include benefit levels, policy changes, race/ethnicity variables, and other economic, policy and demographic variables that might affect the level of welfare usage. Finally, we still need to consider contemporaneous correlation among counties in our aggregate model. This spatial auto-correlation can result when similar forces, such as economic upturns or downturns, affect counties that are located near one another.

We also intend to investigate the anomalous result regarding FG accessions. One approach to this problem will be to improve the specification of our model for the aggregate data, but we suspect that the best approach will be to use the micro-level data to study FG accessions in more detail. These data will allow us to see whether FG accessions increase during the summer because U cases are moving over to FG status.

Later steps include measuring the influence of specific economic sectors on welfare dynamics in a more direct way. To this end, we have requested permission to obtain the standard industrial codes of the employers of welfare recipients in our micro-level LDB data set. With this information we can determine the kinds of employment welfare recipients have while on and off welfare. This will enable us to pin-point exactly the type of employment held by seasonal welfare populations. We also plan to link the individual-level welfare data with individual-level data on wages of welfare recipients.[41] We can then determine whether employment rates and income levels for recipients vary by county type.

Another category of future directions for our project relates to our current geographical level of analysis, county type. As previously discussed, focusing solely on county types can cause us to miss important distinctions between counties within a county type. Therefore we have begun to compare the welfare-usage and employment patterns of different kinds of counties within the agricultural and rural county types. For example, since different crops suggest different labor patterns, we might find that an analysis of sub-groupings of agricultural counties based on their main crops reveals interesting dynamics masked at the county type level.

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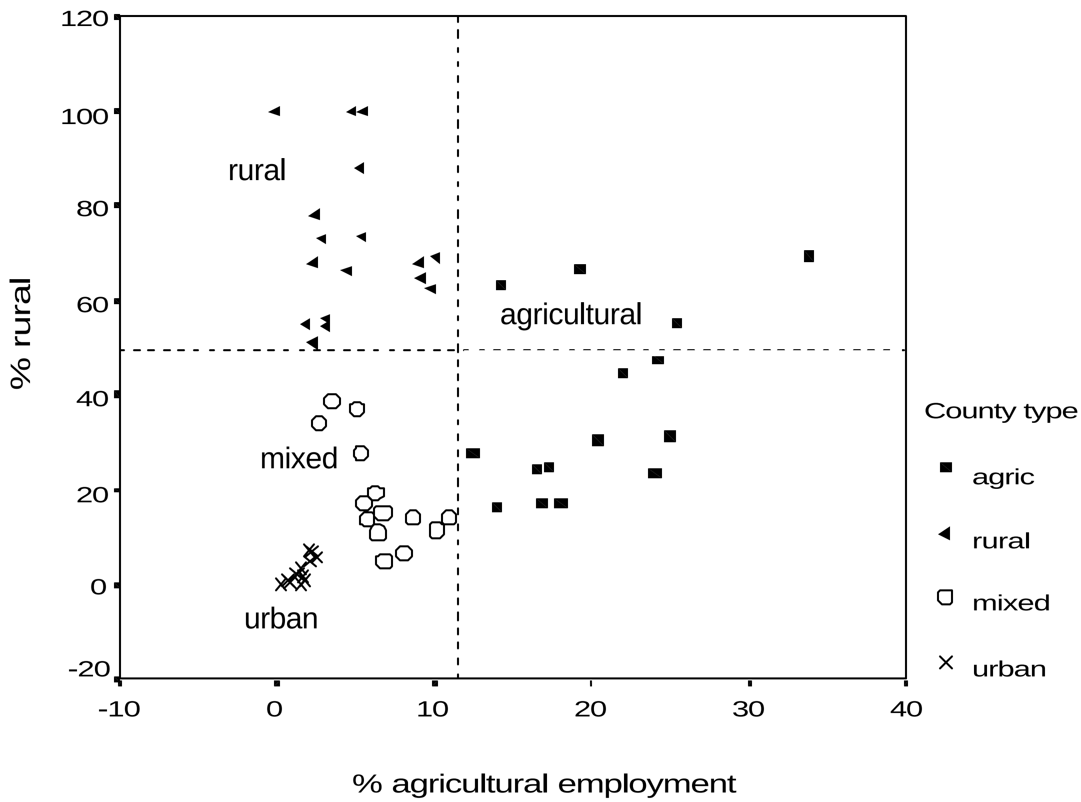
Figure 1: California County Typology



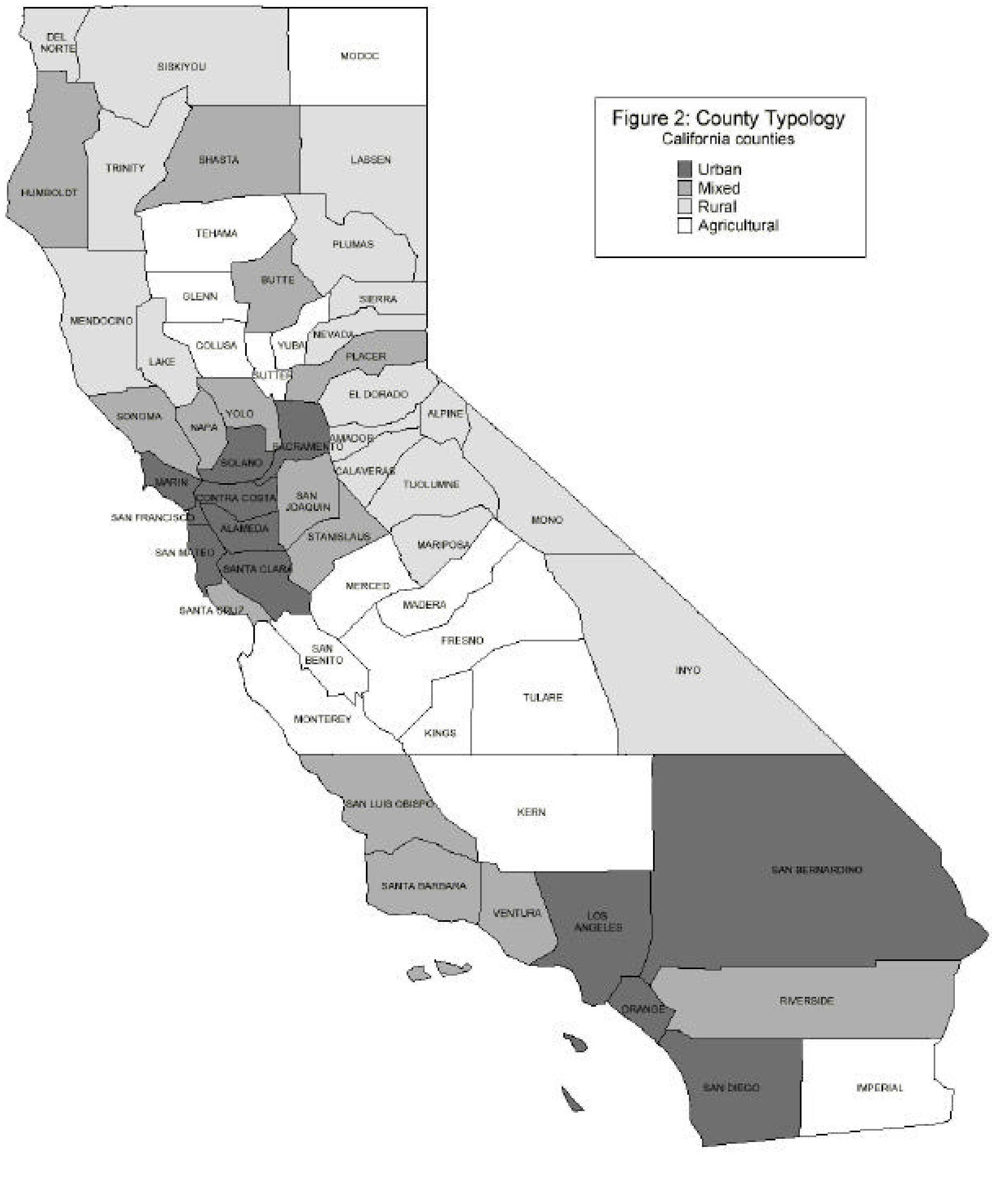


Figure 2: County Typology
California counties
Urban
Mixed
Rural
Agricultural
DEL NORTE
SISKIYOU
MODOC
HUMBOLDT
TRINITY
SHASTA
LASSEN
TEHAMA
PLUMAS
GLENN
BUTTE
SIERRA
MENDOCINO
COLUSA
YUBA
NEVADA
LAKE
SUTTER
PLACER
EL DORADO
SONOMA
NAPA
YOLO
ALPINE
SACRAMENTO
AMADOR
SOLANO
CALAVERAS
MARIN
CONTRA COSTA
SAN JOAQUIN
TUOLUMNE
SAN FRANCISCO
ALAMEDA
STANISLAUS
MONO
SAN MATEO
MARIPOSA
SANTA CLARA
MERCED
SANTA CRUZ
MADERA
FRESNO
SAN BENITO
INYO
TULARE
MONTEREY
KINGS
SAN LUIS OBISPO
KERN
SAN BERNARDINO
SANTA BARBARA
VENTURA
LOS ANGELES
ORANGE
RIVERSIDE
SAN DIEGO
IMPERIAL

FIGURE 3
Unemployment Rate and Percent on Aid, by County Type

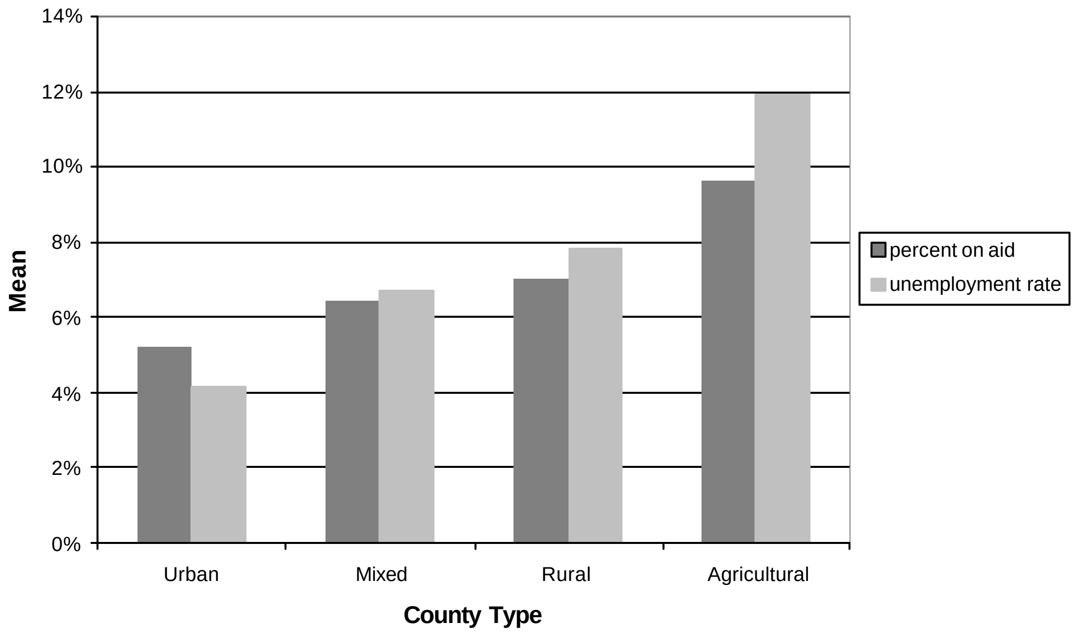


FIGURE 4
Variability of Unemployment Rate and Percent on Aid, by County Type

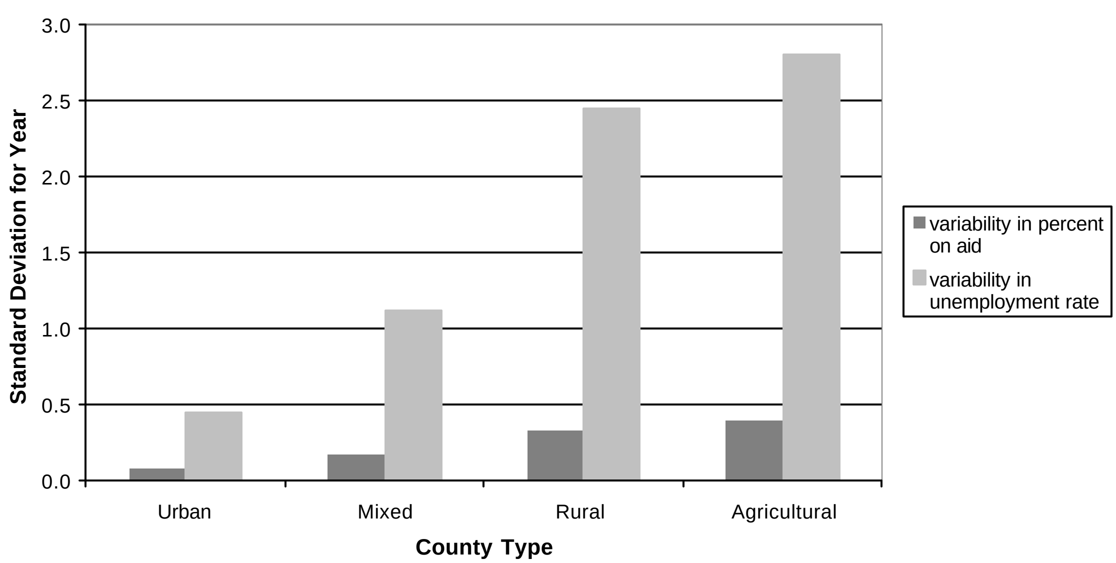


Figure 5: Accession and Termination Rates by Calendar Month

in Agricultural Counties (U cases)

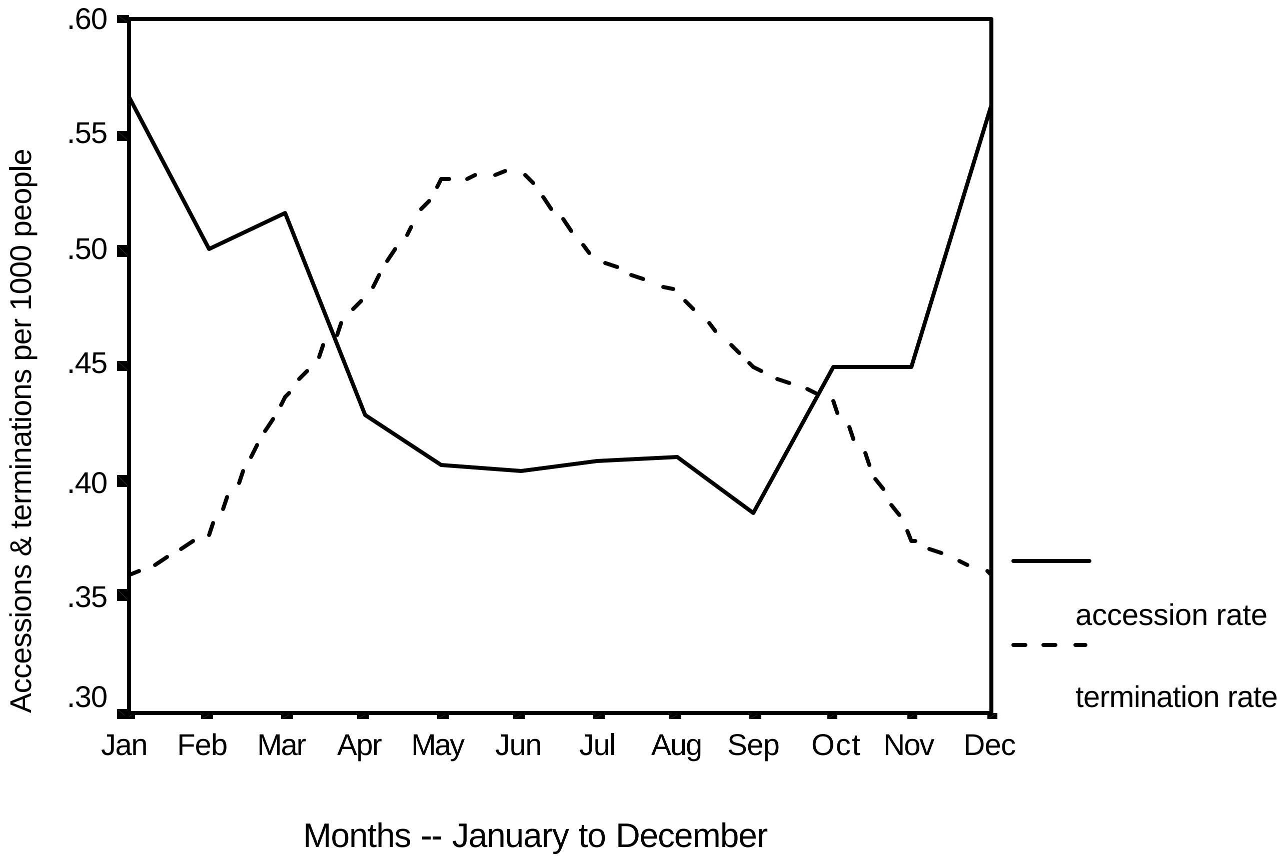


Figure 6: Net New Cases by County Type and Calendar Month

(U cases)

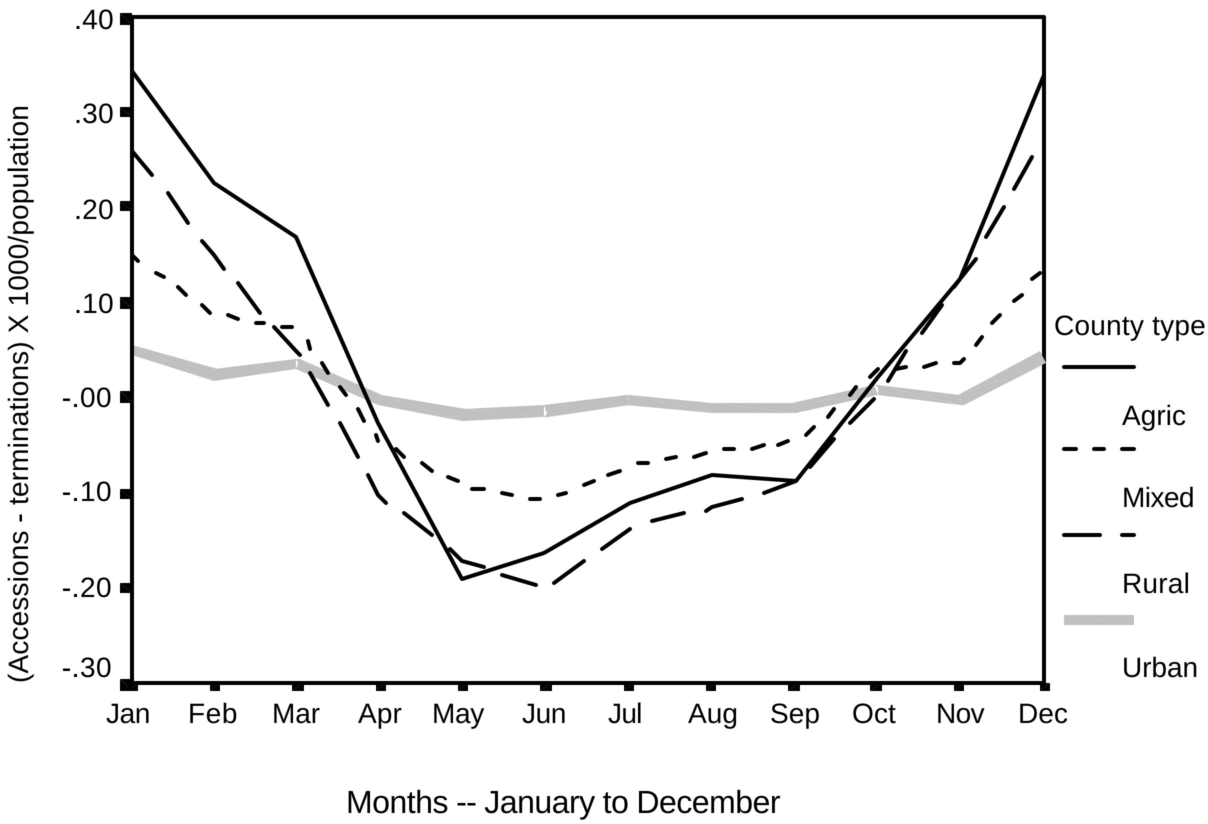


Figure 7: Net New Cases by County Type and Calendar Month

in Agricultural and Urban Counties (FG cases)

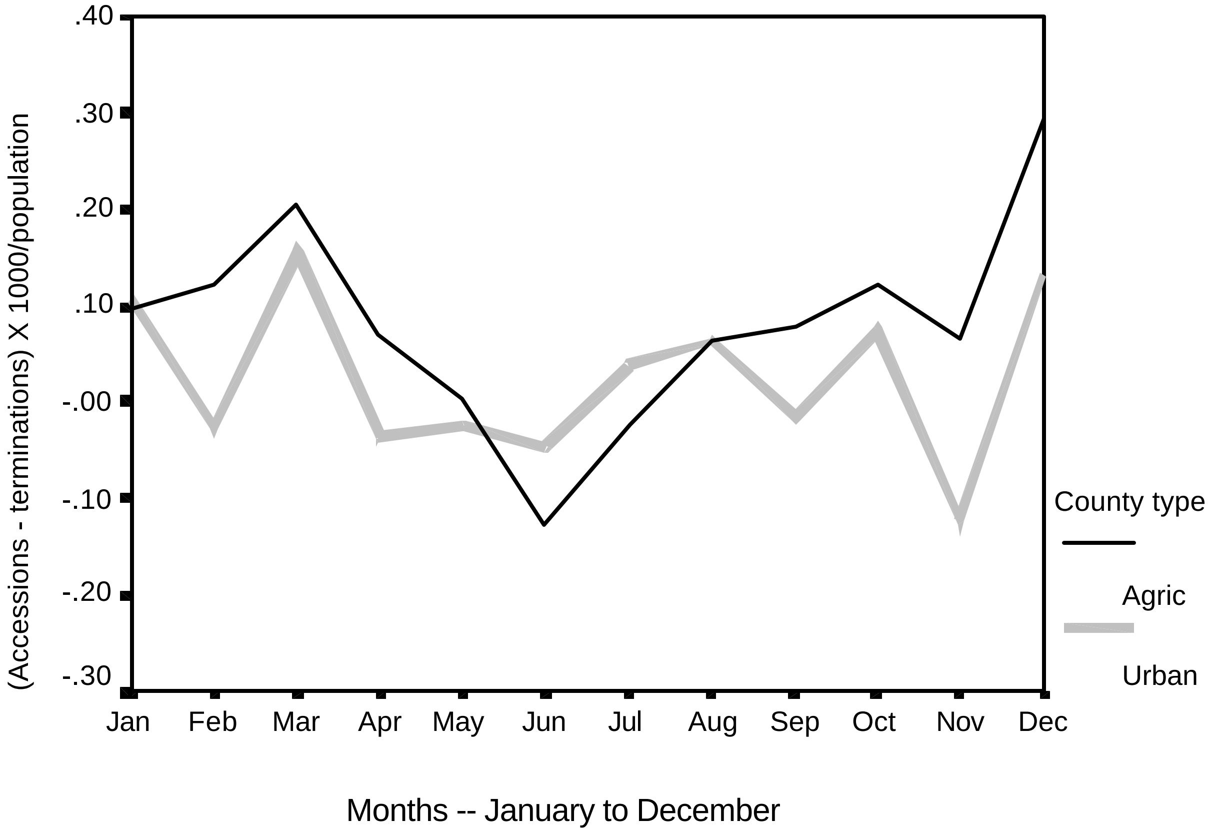


Figure 8: Net New Cases by County Type and Calendar Month

in Mixed and Rural Counties (FG cases)

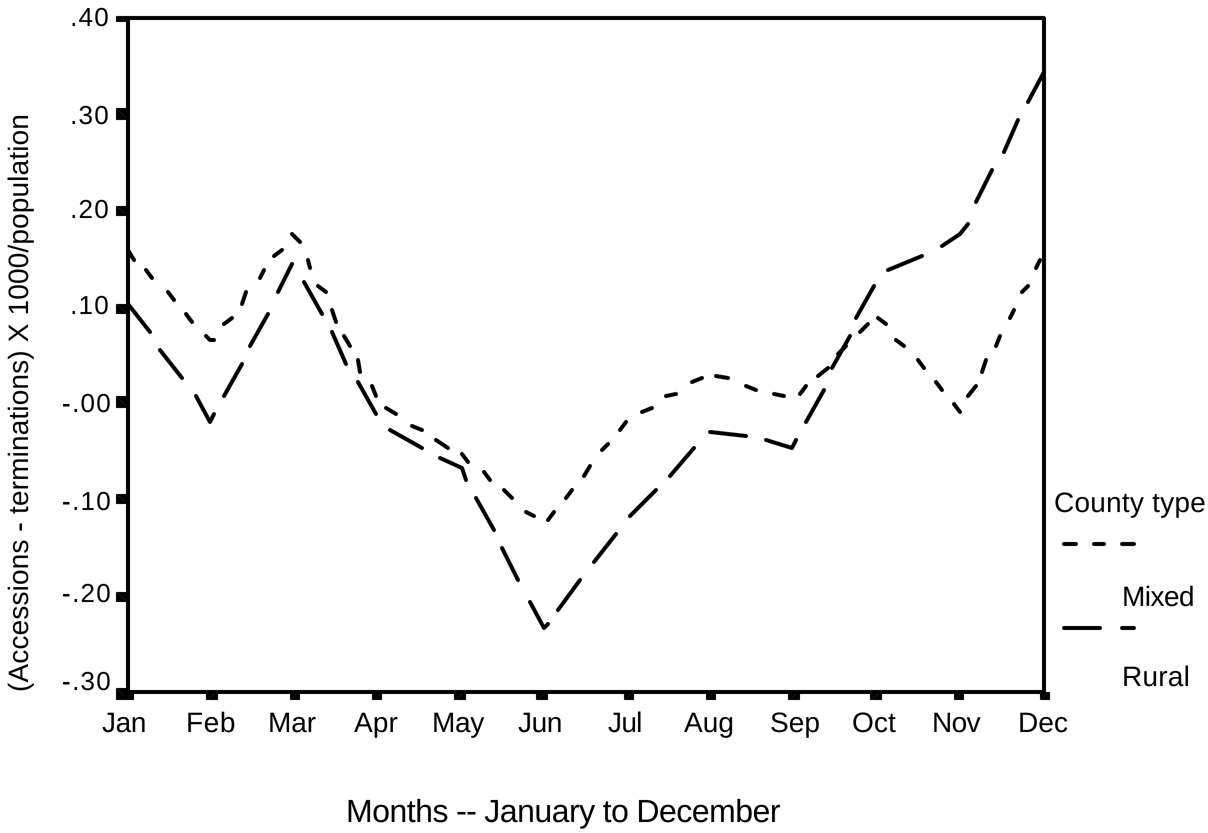


Figure 9: Farm Employment by County Type and Calendar Month

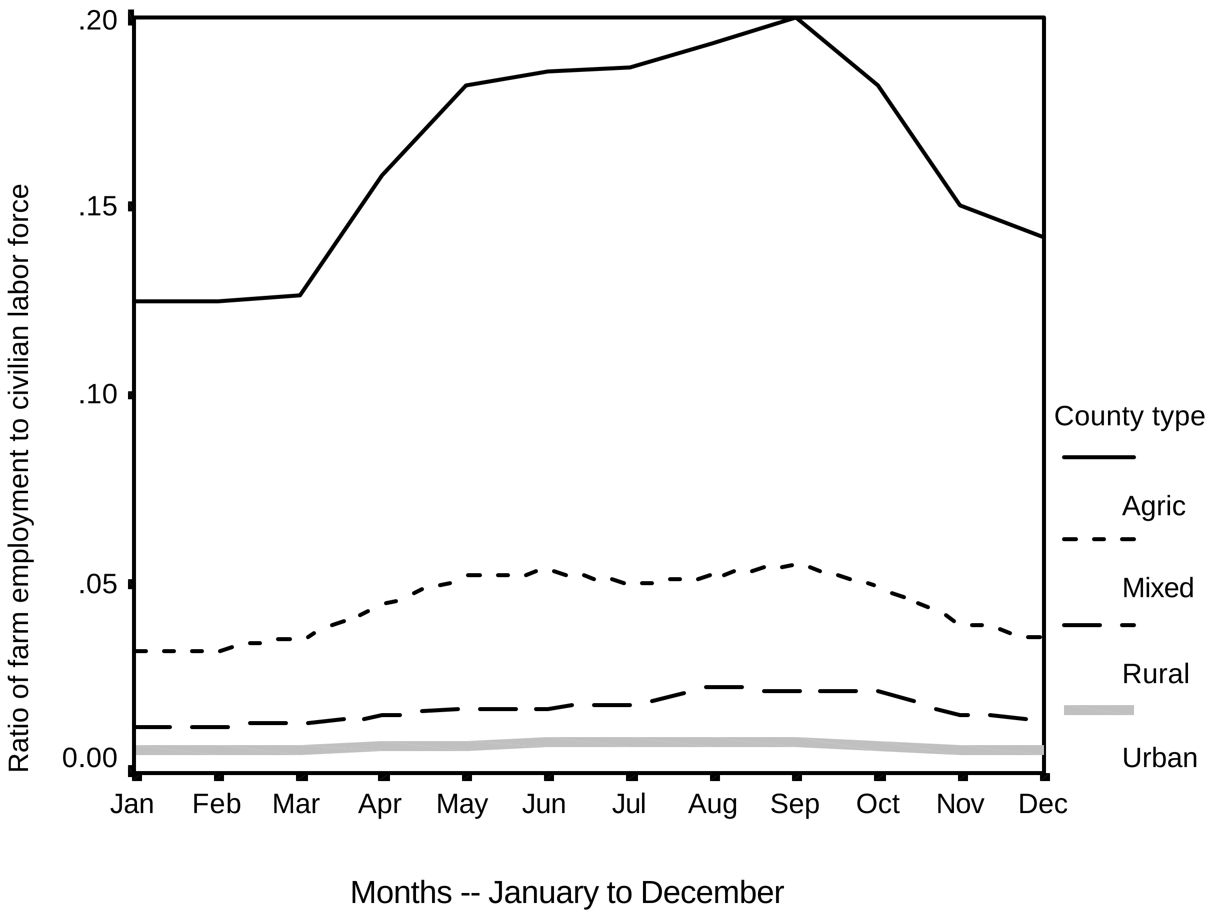


Figure 10: Retail Employment by County Type and Calendar Month

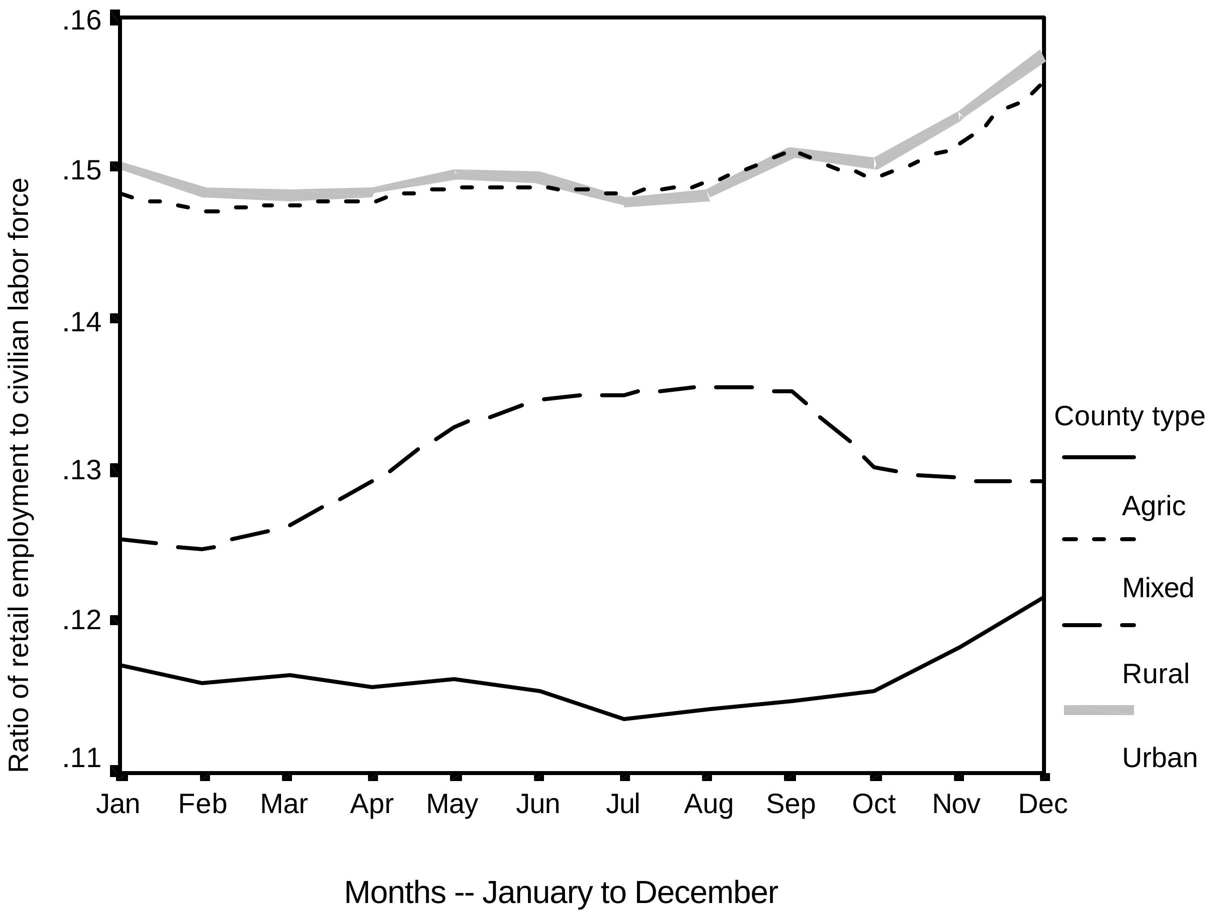


Figure 11: Other Employment by County Type and Calendar Month

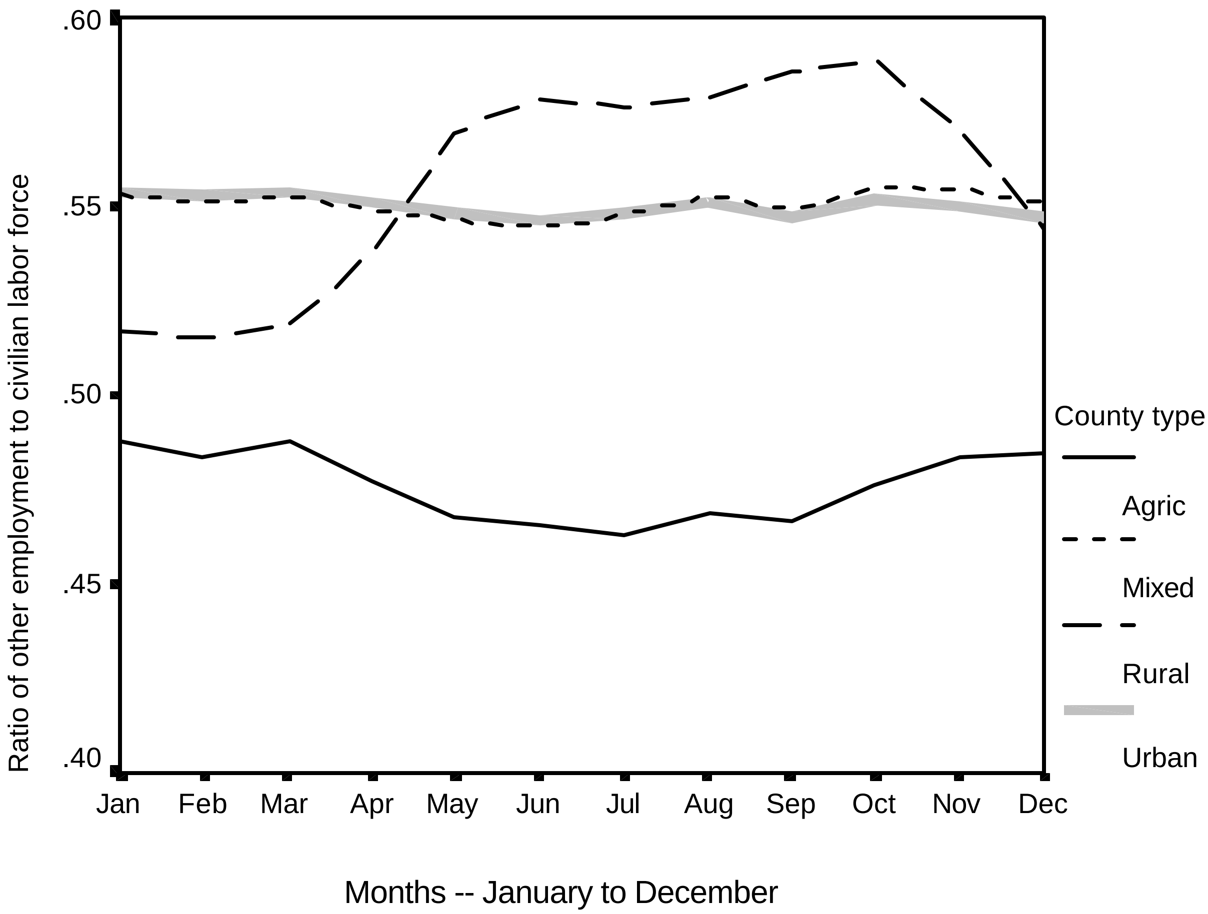


TABLE 1
Determinants of Terminations and Accessions for U and FG Cases
Models with Lagged Dependent Variables

	TRU	**TRFG**	**ARU**	**ARFG**
One lag dependent	.311***	.277***	.3042***	.2776***
Two lags dep.	.183***	.191***	.1897***	.2224***
Three lags dep.	.102***	.204***	.1307***	.1990***
Four lags dep.	.080***	.088***	.0834***	.0860***
Farm	.243***	.040**	-.0075***	.0030
Farm lag one	-.017	-.022	-.0038***	-.0067**
Farm lag two	-.151***	-.018	.0058***	.0017
Farm lag three	-.091*	.012	.0062***	.0021
Retail	.322***	.145***	-.0035	-.0017
Retail lag one	-.137	-.141**	-.0118***	-.0072
Retail lag two	-.052	-.000	.0057*	.0045
Retail lag three	-.003	.020	.0081**	.0041
Service	.070	.081*	-.0069***	-.0010
Service lag one	.191	-.058	-.0040*	-.0053
Service lag two	-.266*	-.051	.0059**	.0019
Service lag three	-.011	.042	.0025	.0038
Other emp.	.209***	.045**	-.0078***	-.0010
Other emp. lag one	-.045	-.031	-.0047***	-.0063*
Other emp. lag two	-.187***	-.051*	.0061***	.0002
Other emp. lag three	-.072	.013	.0050***	.0052*
Fraction with births	X	X	.0082***	.0051
Ag X Summer	.006***	.002**	-.0002***	.0002**
Ru X Summer	.009***	.005***	-.0000	.0003***
Mx X Summer	.004***			

Same models as above but without employment or birth variables

Ag X Summer	.012***	.003***	-.0004***	.0002*
Ru X Summer	.015***	.005***	-.0002***	.0002*
Mx X Summer	.006***	.003***	-.0001***	.0001

* $p \leq .05$, ** $p \leq .01$, *** $p \leq .001$

All estimations are with county and time fixed effects but without any lagged dependent variables and with only a correction for county heteroscedasticity.

TABLE 2
Determinants of Terminations and Accessions for U and FG Cases
Models without Lagged Dependent Variables

	TRU	**TRFG**	**ARU**	**ARFG**
Farm	.247***	.045**	-.0077***	.0025
Farm lag one	.088	-.010	-.0064***	-.0056***
Farm lag two	-.077	-.010	.0018	.0008
Farm lag three	-.050	.029	.0043**	.0024
Retail	.305**	.150**	-.0057**	-.0083
Retail lag one	- .050	-.130*	-.0129***	-.0066
Retail lag two	- .016	.010	.0003	.0029
Retail lag three	.060	.035	.0060*	.0015
Service	.139	.049	-.0088***	-.0073**
Service lag one	.224	-.019	-.0063**	-.0050
Service lag two	-.168	-.079	.0026	.0013
Service lag three	.011	.065	.0010	.0019
Other emp.	.206***	.038	-.0095***	-.0049*
Other emp. lag one	.051	-.005	-.0072***	-.0060*
Other emp. lag two	-.121	-.048	.0021	-.0008
Other emp. lag three	-.066	.019	.0033*	.0037
Fraction with births	X	X	.0265***	.0266***
Ag X Summer	.008***	.003***	-.00029***	.00011
Ru X Summer	.017***	.007***	-.00012**	.00016
Mx X Summer	.010***	.004***	-.00003	.00010

Same models as above but without employment or birth variables

Ag X Summer	.018***	.004***	-.00078***	.00003
Ru X Summer	.026***	.008***	-.00037***	-.00002
Mx X Summer	.014***	.005***	-.00016***	.00008

* $p \leq .05$, ** $p \leq .01$, *** $p \leq .001$

All estimations are with county and time fixed effects but without any lagged dependent variables and with only a correction for county heteroscedasticity.

TABLE 3: Means & Standard Deviations for County-level Data

Variable	County Type				
	Urban	Mixed	Agricultural	Rural	All
Termination rate (U)	.074 (.029)	.119 (.053)	.106 (.055)	.127 (.068)	.109 (.058)
Termination rate (FG)	.070 (.021)	.078 (.024)	.063 (.022)	.077 (.028)	.072 (.025)
Accession rate (U)	.0010 (.0006)	.0019 (.0011)	.0037 (.0020)	.0031 (.0022)	.0025 (.0020)
Accession rate (FG)	.0055 (.0028)	.0068 (.0029)	.0096 (.0044)	.0090 (.0045)	.0079 (.0041)
Farm employment fraction	.007 (.004)	.044 (.028)	.163 (.078)	.018 (.021)	.057 (.074)
Retail employment fraction	.150 (.017)	.149 (.020)	.116 (.020)	.137 (.049)	.138 (.034)
Service employment fraction	.239 (.084)	.175 (.033)	.105 (.035)	.147 (.071)	.163 (.075)
Other employment fraction	.549 (.092)	.550 (.049)	.476 (.109)	.601 (.106)	.547 (.103)
Unemployment rate	.055 (.017)	.081 (.031)	.140 (.053)	.097 (.037)	.095 (.048)
% At-risk women with births in last year	.070 (.011)	.068 (.010)	.087 (.010)	.061 (.010)	.071 (.014)
Number of observations	*1566*	*1938*	*1833*	*2220*	*7557*

Note: Standard deviations in parentheses

Table 4: Estimation of Discrete-Time Hazard Models

	One-parent (FG)		Two-parent (U)	
	#1 no employment	#2 employment	#3 no employment	#4 employment
County type * summer interactions				
summer*agric	.0028 (.0016)	.0016 (.0020)	.0078 *** (.0024)	.0045 (.0029)
summer*mixed	.0007 (.0019)	-.0007 (.0020)	.0128 *** (.0029)	.0092 ** (.0031)
summer*rural	.0089 * (.0041)	.0065 (.0043)	.0311 *** (.0068)	.0238 *** (.0071)
baseline: summer * urban	0 (--)	0 (--)	0 (--)	0 (--)
Employment				
farm	--	.2752 *** (.0492)	--	.2457 *** (.0706)
retail	--	.2640 (.1754)	--	.5958 * (.2702)
service	--	.4552 *** (.1314)	--	-.0353 (.2085)
other	--	.3150 *** (.0635)	--	.3599 *** (.0940)

* $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$

n=468,418 (one-parent spell-month records), 188,357 (two-parent spell-month records)

Notes: All equations are OLS discrete-time hazard models with controls for age, spell duration effects, and month-of-year and county fixed effects. Entries are unstandardized regression coefficients with standard errors in parentheses. The dependent variable, exit, is coded as follows: 0 = did not exit welfare, 1 = exited welfare. The time period covered is April 1987 to August 1997.

[1] We define summer months as May through October and winter months as November through April.

[2] And the value of agricultural production in California is somewhat larger than that of the four agricultural states of Iowa, Kansas, Missouri, and Nebraska combined.

[3] The mixed counties have a combined population that is greater than forty states, and the combined population of the urban counties alone is about one-third larger than any other state.

[4] The Council of Economic Advisers uses annual state panel data (1976-96) to estimate their OLS regression model of percent of population on aid. They control for contemporaneous and one-year lagged unemployment rate, welfare benefit level, federal welfare waivers, lead effect for waivers, state and year fixed effects, and state-specific time trends. Ziliak et al. use monthly state panel data (1987-96) to estimate their OLS regression model of per capita caseload. They control for six lagged values of the dependent variable, the contemporaneous and 11 lagged values of employment per capita, federal welfare waivers, implementation lag for waivers, state and month-of-year fixed effects, and a quadratic trend.

[5] Blank uses a weighted OLS procedure, where weights are based on state population, to estimate her models for 1977-95. The dependent variables are cases divided by women age 15-44 for one-parent caseload, and log of two-parent cases for two-parent caseload. She controls for the contemporaneous and two lagged values of the unemployment rate, median wage, wages at the 20th percentile of the wage distribution, AFDC benefit level, existence of AFDC-UP program (for one-parent household model only), average family Medicaid expenditures, federal welfare waivers, education level, percent African-American, percent single female heads of households, percent elderly, immigrants, party of governor, party controlling both state House and Senate, and fixed state and year effects.

[6] The accession rate is (accessions / number of women age 15-44 not receiving welfare benefits); the termination rate is (terminations / caseload). The equations control for contemporaneous and two lagged values of the unemployment rate, nonagricultural employment growth, California minimum wage, potential earnings for a representative low-skilled male worker (for two-parent equations) and female worker, birth rate, race/ethnic composition, immigration, policy changes, combined AFDC and Food Stamp benefit amount, average caseload size, proportion of caseload with no adult on budget, one lagged value of dependent variable for the one-parent accession equation and both termination equations, six lagged values of termination rates (for accession equations), six lagged values of accession rates (for termination equations), and month-of-year fixed effects.

[7] The dichotomy used by researchers rarely corresponds to the urban-rural distinction devised by the Census Bureau, in which an area is “urban” if it has a “place” (e.g., city, town) of at least 2,500 people. Most researchers use a definition of urban that is less encompassing.

[8] Her point-in-time study includes 68 local labor-markets (29 rural, 39 urban) formed from 584 counties and county equivalents. The labor market areas are based on commuting patterns of workers.

[9] Their sample includes census tracts contained in 65 towns with populations between 10,000 and 20,000 and with 8 percent or more of their work forces employed principally in agriculture.

[10] The new book edited by Sheldon Danziger, *Economic Conditions and Welfare Reform* (1999, Kalamazoo: W. E. Upjohn Institute for Employment Research), contains a number of chapters that are relevant to our research. We have read the first chapter that summarizes the book by going to the following website: (http://www.upjohninst.org/publications/titles/ecwr.html), but we have not yet obtained a copy.

[11] Percent rural figures are from the U.S. Bureau of the Census, *Census of Population and Housing, 1990*. They indicate the percent of the population who lives in rural areas, defined as all areas except places of 2,500 or more population incorporated as cities, villages and towns. Percent farm and agricultural services employment figures are for 1993, from the U.S. Bureau of Economic Analysis.

[12] Anonymous reviewers of our grant proposal to the California Policy Research Center raised some concerns about our county typology. It was suggested that a classification scheme based on a lower level of aggregation than county might be more fruitful, since significant welfare and employment dynamics could get lost in the aggregation. Our results suggest that the current typology is quite meaningful. Focusing on counties is also desirable since welfare programs are administered by counties, and the scheme allows us to consider the influence of specific economic sectors on welfare dynamics. Another reviewer stated that we might miss important distinctions between counties within a county type. Indeed we have already begun to compare the welfare-usage and employment patterns of different kinds of counties within the agricultural and rural county types. Since different crops suggest different labor patterns, one subgrouping of agricultural counties might be based on their main crops. Another subgrouping might be by percent rural population, as farm workers in more urbanized counties would seem to have an easier time finding employment in the off-season than those in less urbanized areas. Rural counties might also be classified by their economic bases because counties with seasonal industries, such as tourism, are more likely to have seasonal welfare populations.

[13] We have compared our classification scheme to two alternative classification systems from the U.S. Department of Agriculture: Beale Code definitions and ERS economic function types. To a large

extent, our typology accords with these alternative classifications. The biggest differences are that we are much less likely to classify counties as metropolitan, and we have a less stringent requirement for calling a county "agricultural" than the ERS requirement for "farming."

[14] The numbers are simple averages across counties, rather than weighted averages taking into account the different population of each county.

[15] Variability is calculated as the standard deviation of monthly figures within a year.

[16] Our finding of higher welfare participation in nonurban areas is consistent with Fuguitt, Brown and Beale (1989). They find that 8.6% of all nonmetropolitan households in the 1980 Census rely on public assistance compared to 7.8% of metropolitan households. The opposite is true for welfare participation among impoverished households. Using the 1998 Current Population Survey, RUPRI (1999) finds that a greater percentage of households below 125% of the poverty level get public assistance in urban areas (13%) than in the suburbs (10%) and nonmetropolitan areas (8%).

[17] Two-parent families accounted for about one-sixth of the average monthly caseload in rural (15.6%), urban (16.4%), and mixed counties (16.5%) in 1997. Almost one-quarter (22.7%) of the caseload in agricultural counties were comprised of these families. Compared to other states California has a disproportionate share of its caseload comprised of two-parent families; only seven percent of the national caseload consisted of these families in 1996. More than half of all two-parent cases (54%) were in California in 1996. (*1998 Green Book)*

[18] Retail employment includes general merchandise, food stores, eating and drinking places, and other retail trade. Therefore, we would expect retail employment to be responsive to seasonal tourism.

[19] We could assume heterogeneity within a group so that the probability of an accession for any member of group k would be $(b_{itk} + \delta_{itk})$ with a mean of b_{itk}. We make a variant of this assumption in equation (8).

[20] Alternatively, we could include them but assign a zero for their value of b_{itk}, but this approach only complicates the estimation problem without adding anything.

[21] It could even be the size of the caseload if we thought that the probability of accessions, say, decreased for the at-risk group as those predisposed to go on welfare had already entered the program.

[22] This result may not be immediately obvious, but the zero mean of ψ_{itk} and the assumption that it is independent of (and not just uncorrelated with) c_i, e_t, X_{itk} and d_{itk} is sufficient to insure this result.

[23] We must also drop one of the c_i and e_t terms for identification.

[24] We would not expect weighted least squares to do better because 99.7 percent of the variance in population is explained by county and allowing variances to vary by county provides more degrees of freedom than simply allowing it to vary with some power of population.

[25] These counties are so small that employment data are not always available for them.

[26] These counties are: Alameda, Contra Costa, Inyo, Marin, Mono, Napa, Riverside, San Bernardino, San Francisco, San Mateo, and Solano.

[27] The two groups were obtained as follows. The number of women age 15-44 who gave birth in the last year is assumed to equal the number of children age 0. The number of women age 15-44 who did not give birth in the last year is assumed to equal the total number of women age 15-44 minus the number of children age 0. This approach ignores multiple births and the possibility of some infant mortality. It also ignores the fact that some children are born to mothers already on welfare, and some 15, 16, and 17-year-old women at risk of pregnancy are in their mothers' cases. It also fails to adjust for births for mothers younger than 15 and older than 44.

[28] The web site is (www.dof.ca.gov/html/Demograp/data.htm). The data are referenced as: "Race/Ethnic Population with Age and Sex Detail, 1970-2040." Sacramento, CA, December 1998.

[29] We assumed that the number of women on welfare equaled the total caseload, and we subtracted this number from the number of women age 15-44 before constructing our two at-risk groups.

[30] The web site is (www.calmis.ca.gov/htmlfile/subject/indtable.htm).

[31] We use data from both sources. For example, the farm employment data are industry data and the series on the civilian labor force is labor force data. According to the LMID, "In most geographic areas, the difference between the employment in labor force statistics and the industry employment is minimal."

[32] We still must perform some formal tests to support this assertion, but a visual inspection of the residuals suggests that virtually all of the very obvious and substantial heteroscedasticity in the residuals from OLS estimations is eliminated by allowing for county specific error variances.

[33] The log-likelihoods do increase significantly, however, if we correct for panel specific auto-regression. We have chosen not to do this because the auto-regressive parameters vary so much from one panel to another suggesting that we might be over-fitting the data. In addition, this correction does not change the results in any way.

[34] These decisions were made by inspecting the pattern of coefficients on additional lags and by undertaking log-likelihood ratio tests to see if additional lags were statistically significant.

[35] The number of births in the fraction include births to women both on and off welfare, because we are unable to distinguish between the two groups. Ideally, only births to women who do not receive welfare would be included.

[36] In fact, the standard errors appear to be about the same in both models.

[37] The result is weaker on Table 1, even after adjusting for the inclusion of lagged dependent variables.

[38] Hoynes used the 1 percent cases sample of the LDB for her 1996 paper on the effect of local labor markets on welfare spells. Many of our modeling decisions are similar to those she made for that paper.

[39] Previous research also finds that welfare spells are longer in urban areas (O=Neill et al. 1987, Rank and Hirschl 1988, Porterfield 1998).

[40] As before, we define summer months as May through October and winter months as November to April.

[41] For this and other micro-level analysis of welfare recipient wage patterns we will use another dataset

created by UC DATA under contract with the California Department of Social Services. This data set, "Wages: Statewide Longitudinal Database – Persons," has employment information (wages and number of employers, per quarter) for each person in the 10 percent sample of all Medicaid eligible persons in California for 1987 through 1997.