The Review *of* Economics *and* Statistics

VOL. LXXXII AUGUST 2000 NUMBER 3

LOCAL LABOR MARKETS AND WELFARE SPELLS: DO DEMAND CONDITIONS MATTER?

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Abstract—This paper examines the impact of changes in labor market conditions on participation in the Aid to Families with Dependent Children (AFDC) program in California. Transitions off welfare and transitions back onto welfare are estimated using discrete duration models that control for local labor market conditions, demographic and neighborhood characteristics, duration effects, county-fixed effects, time effects, and county-specific time trends. The results show that higher unemployment rates, lower employment growth, lower employment-to-population ratios, and lower wage growth are associated with longer welfare spells and higher recidivism rates. Hispanics, blacks, and two-parent families are the groups that are most sensitive to changes in local labor market conditions.

I. Introduction

MANY important changes in the U.S. welfare system are currently taking place in response to recent federal welfare reform legislation.[1] While there exists very divergent views as to how these reforms should be implemented at the state level, there seems to be a consensus that employment should play a central role in reducing reliance on public assistance. Most states have reformed their Aid to Families with Dependent Children (AFDC) programs to increase the work activities of recipients either through mandatory work programs, training programs, or time limits on benefits. However, despite the belief that pursuing employment strategies will reduce welfare dependency, little is known about the factors that contribute to achieving independence.

What we do know is that employment has become an important factor in facilitating transitions off welfare.[2] Recent studies have shown that a change in the employment status of the mother is the characteristic most commonly associated with an exit from welfare, accounting for as much as one half of exits among AFDC recipients (Blank, 1989; Blank & Ruggles, 1996; Fitzgerald, 1995; Gritz & MaCurdy, 1992; Harris, 1993; Pavetti, 1993).[3] However, remarkably little is known about the factors that determine these exits from welfare. The literature has examined the importance of supply-side factors such as education, family structure, job training and placement programs, and the availability of transitional benefits for child care and medical care. The literature has also examined the role of program incentives such as the benefit level and implicit tax rate on earned income. At the same time, we would also expect that local labor market conditions, reflected in average wage levels and employment opportunities, would affect the length of time on welfare through offer wages and job availability. These demand-side factors have received little attention in the literature.

Understanding the link between macroeconomic conditions and welfare utilization is important for several reasons. First, to what extent can economic growth alone reduce welfare reliance? Can a regime of high employment growth and increasing real earnings significantly reduce the size of the welfare rolls? Second, should time limits of welfare benefits be relaxed in economic downturns? Unemployment benefits are initially limited to a period of 26 weeks but are extended for an additional period if a state has relatively high unemployment rates. Linking time limitations in welfare receipt to local unemployment rates was discussed but abandoned in part because the empirical research provided no compelling evidence that supports a link between local labor markets and welfare dependency. Last, with federal support for AFDC programs now taking the form of a block grant, states will incur more risk associated with business-cycle fluctuations.

Most of the available evidence on the links between labor demand and welfare utilization comes from caseload studies. Examining the impact of labor market conditions using micro data has been hampered by significant data limitations. First, because of confidentiality concerns, survey data sets typically do not allow for identification of local labor

Received for publication June 17, 1996. Revision accepted for publication August 3, 1999.

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I am grateful for the useful comments of Timothy Bartik, Becky Blank, David Card, Nada Eissa, Jonathan Gruber, Larry Katz, Jacob Klerman, Jonathan Leonard, Robert Moffitt, Jim Poterba, Jim Powell, two anonymous referees, and of the seminar participants at Columbia, Dartmouth, Harvard, MIT, Princeton, Yale, and workshops at RAND, IRP, and the NBER Summer Institute. I also would like to thank Lois Van Beers, Susan Ayasse, Henry Brady, and Werner Schink for assistance with the LDB data. Cindy Gustafson and Darren Lubotsky provided excellent research assistance. Financial support was received from the Sloan Foundation and the National Institute for Child Health and Human Development. Computing support was provided by the Econometrics Laboratory at UC Berkeley.

[1] The Personal Responsibility and Work Opportunity Reconciliation Act of 1996 (PRWORA) created the Temporary Assistance for Needy Families (TANF), which replaces AFDC.

[2] The terms ***AFDC*** and ***welfare*** will be used interchangeably.

[3] Earlier work found that marriage was the most common route off welfare (Bane & Ellwood, 1983). Marriage may represent a more permanent route off welfare, as those exiting via work are more likely to return to welfare (Pavetti, 1993).

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markets, relying instead on larger geographical areas that might not accurately capture labor market opportunities. Second, survey data generate relatively small samples of welfare recipients, making it difficult or infeasible to include controls for labor market fixed effects, which may be important.

This study uses administrative data to present new and superior estimates of the effect of local labor markets on AFDC participation. The Longitudinal Database (LDB) is a 1% sample of all AFDC cases in California and contains monthly welfare utilization information between 1987 and 1992. The data allow for identification of county of residence (which is used to assign local labor markets). Models of exit from welfare and reentry to welfare are estimated using discrete duration models that control for demographic characteristics, duration effects, local labor market variables, and neighborhood characteristics. We consider several measures of labor markets including unemployment, employment, employment-to-population ratios, and average earnings. We also control for fixed county and time effects as well as county-level linear trends resulting in estimated labor market effects that are identified by differences in the timing and severity of cycles across counties as opposed to average differences in levels or trends across counties.

The results show that higher unemployment rates, lower employment growth, lower employment-to-population ratios, and lower wage growth are associated with longer welfare spells and shorter periods off welfare. The estimates show that a 10% increase in employment or a reduction of 3.5 percentage points in employment-to-population ratios (changes typical of the impact of the recent recession and recovery in California) lead to a 7%–15% increase in the likelihood that an AFDC recipient exits welfare within one year. A 5% increase in average earnings leads to slightly smaller effects, on the order of a 5%–7% increase in the one-year exit rate. The results also show that labor market fluctuations are important determinants of recidivism rates: similar employment (earnings) expansions lead to a 6%–15% (4%–8%) decline in the probability that a family returns to AFDC within one year of leaving welfare. Hispanics, blacks, residents of urban areas, and AFDC-UP (unemployed parent) recipients are more sensitive to changes in labor market opportunities while whites and teen parents are less sensitive. Further, the results show that models that control for labor market conditions using employment-based measures perform better than unemployment rates.

The remainder of the paper proceeds as follows. Section II presents the economic motivation, and section III reviews the literature on the economic effects of local labor market conditions on welfare and employment. Section IV describes the data, and section V describes the empirical model. The results are presented in section VI, while section VII concludes.

II. Conceptual Framework

Changes in employment and marital status are the two most important events associated with movements on and off welfare (Bane & Ellwood, 1983; Blank, 1989; Blank & Ruggles, 1996; Fitzgerald, 1995; Gritz & MaCurdy, 1992; Harris, 1993; Pavetti, 1993). To examine the role that local labor market conditions play in welfare-participation decisions, consider each of these two factors in turn. To simplify the discussion, assume that welfare recipients do not work while on the rolls and that welfare is available only for unmarried parents.[4]

First, local labor markets affect employment decisions of welfare recipients, thereby changing welfare participation. The static model of labor supply and welfare assumes that individuals maximize utility by making choices about labor supply and program participation subject to a budget constraint that takes into account wage opportunities and welfare benefits. Utility is a function of leisure, income, and possibly welfare stigma (Moffitt, 1983). Welfare participation is chosen if the indirect utility of the welfare choice is greater than the indirect utility of being off welfare. Increases in earnings available off welfare will increase the likelihood that the welfare state is not chosen. Local labor market conditions affect this in two ways: lower unemployment rates and higher employment growth increase the likelihood of obtaining work, and increases in area wages increase the potential return to working.

Second, local labor markets can affect marriage decisions, thereby changing welfare participation. Models of marriage, based on the work of Becker, argue that unions occur when, for both parties, the utility of marriage outweighs the utility outside marriage (Becker, 1981). This model implies that higher earnings possibilities among potential spouses will increase a woman's gain to marriage. If marriage is seen as an alternative to welfare, then increases in the earnings of potential mates will reduce welfare participation. Local labor market conditions are relevant here as well, in that increases in job availability will increase the likelihood of work for the potential spouse, and increases in area wages will increase their earnings opportunities. Both increase the quality of the marriage market.

A natural way to build dynamics into the static welfare-participation model is to add job search and marital search components.[5] Within a search framework, local labor market conditions will affect welfare participation by increasing the frequency and quality of job offers given a level of search intensity.

In sum, local labor market conditions will influence welfare-participation decisions through two channels. Increases in local area wages will increase the earnings for

[4] These assumptions are for convenience and do not change the implications derived in the discussion.

[5] Gottschalk (1988) applies a standard job search model to a model of welfare participation.

both working women and their potential spouses, thereby reducing welfare participation. Increases in the local availability of jobs will increase work by women and their potential spouses through increases in the frequency of job offers and stability of employment, also resulting in lower welfare participation. Therefore, increases in our measures of earnings and employment are expected to lead to lower welfare participation through increases in exits from welfare and decreases in returns to welfare.

III. Literature Review

Most studies of welfare dependency examine the determinants of exits from welfare, while a much smaller group of studies examine the determinants of returns to welfare.[6] The typical study includes controls for demographic characteristics, AFDC benefits, and length of spell. Some studies of exits from welfare control for job opportunities by including the state unemployment rate and/or state average wage and find that these coefficients are small and statistically insignificant (Bane & Ellwood, 1983; Blank & Ruggles, 1996; Fitzgerald, 1991; Hoynes & MaCurdy, 1994; O'Neill, Bass, & Wolf, 1987; O'Neill, et al., 1984; Plotnick, 1983).[7] This may be because the state is too large an area, thus leading to mismeasurement of true labor market opportunities. A few studies use counties (or grouped counties) to assign labor market controls and find insignificant (Blank, 1989) or small (Fitzgerald, 1995; Harris, 1993; Sanders, 1992) effects. For example, Fitzgerald uses a sample of female heads of household from the SIPP and assigns labor market data using counties grouped into 88 "labor market areas." He finds that areas with lower unemployment rates are associated with shorter spells for blacks, but that whites are not significantly affected.[8] Among studies that examine returns to welfare, Harris (1996), Meyer (1993), and Pavetti (1993) include controls for county unemployment rates, but none of these estimates provides large or statistically significant results.

In these studies, the effect of the labor markets is identified primarily from differences across areas in labor market conditions. If any omitted area characteristics are correlated with the labor market variables, the results will be biased. For example, individuals with low education levels and little labor market experience may be more likely to live in areas with adverse labor markets. Other omitted variables such as differences in the cost of living and county services for job placement and job search may also be important.

Fitzgerald (1994) is the only study that controls for area effects. As with his 1995 study, he uses the SIPP and measures unemployment rates for grouped county areas. When he includes labor market area-fixed effects, the coefficient on the unemployment rate becomes small and statistically insignificant for both whites and blacks. He suggests that this may be due to insufficient variation in the labor market conditions over time, but it may also be due to relatively small sample sizes. He pools the 1984 and 1985 SIPP panels, yielding 533 spells of welfare receipt for female heads of household. With this sample, he includes 88 local-area effects.

While the evidence from the welfare spell literature is inconclusive, empirical analyses of aggregate welfare caseloads more consistently find evidence that labor market conditions do indeed matter. Most of the early caseload studies (for an example, see the review by Peskin (1993)) are somewhat limited in that they examine the determinants of the national caseload or the caseload in a particular state, and therefore rely on pure time variation to determine labor market effects. More-recent studies use pooled cross-state data and estimate models that control for state fixed effects, time effects, and state-specific time trends, and find that labor market conditions are important determinants of the welfare caseload (Blank, 1997; Council of Economic Advisors (CEA), 1997; Ziliak, et al., 1997). The CEA study estimates the relative contribution of the unemployment rate and welfare reform to the per capita welfare caseload and finds that an increase of one percentage point in the unemployment rate leads to a 3%–5% increase in the per capita welfare caseload. Blank (1997) extends the CEA study by also considering the importance of AFDC program variables, demographic characteristics, and political factors. Zilliak, et al. (1997) differ from the CEA and Blank studies by using monthly as opposed to annual data. Both Blank and Zilliak, et al. find statistically significant but somewhat smaller effects of labor market conditions than the CEA study does.

For this application, an analysis of micro data (as presented here) is preferred to a caseload analysis for several reasons. First, an analysis of aggregate caseload data does little to reveal why labor markets matter. Using micro data allows the separate examination of the effects of labor market variables on entry into welfare, length of welfare spell, and recidivism. Second, caseload data do not typically allow for separate analyses by subgroups (such as demographic groups). Lastly, and potentially most importantly, because of an inability to control for the mix of the caseload in terms of short and long spells, an analysis of aggregate caseloads may lead to an upward bias in the estimated importance of local labor market conditions. Suppose that average welfare durations increase in a economic downturn. Then, appealing to standard omitted-variable arguments, the coefficient on the local labor market conditions may falsely pick up the effect of the change in mean duration.

[6] The welfare dynamics literature is reviewed in many places; for example, see Moffitt (1992). Here, the review will be limited to the importance of local labor market conditions.

[7] The data sets used for analyses of welfare dynamics include the Panel Study of Income Dynamics (PSID) and the Survey of Income and Program Participation (SIPP) which identify states, and the National Longitudinal Survey of Youth (NLSY) which identifies counties.

[8] The public release version of each of the SIPP data sets identifies only the state of residence. Fitzgerald received access to this confidential data on county of residence while working as a Census Department Fellow.

The discussion in section II concluded that labor market conditions affect welfare participation both through wage levels and the probability of finding and keeping employment. The static welfare participation literature generally finds that higher wages lead to lower rates of participation in welfare (Moffitt, 1992). A few studies of welfare dynamics have included either predicted wages (Plotnick, 1983; Harris, 1996) or earnings prior to starting welfare (Bane & Ellwood, 1983; Hutchens, 1981; O'Neill, et al., 1984) in analyses of exits from welfare. The results generally show a positive association between wage levels and exits from welfare, but in many cases the results are insignificant.[9]

IV. Data and Descriptive Analysis

A. LDB Data

The main data for this study are the Longitudinal Database of Cases (LDB) compiled by UC Data at the University of California, Berkeley, in association with the California Department of Social Services. The LDB data are constructed by taking a 1% sample of all Medi-Cal (California's Medicaid program) cases in January of 1987 plus a 1% sample of all new Medi-Cal cases starting each year from 1987 to the present. (A "new" case is one in which the person has not received Medi-Cal since January of 1987.) The results here are based on the 1992 release of the data, covering the period 1987–1992 (UC Data, 1994).[10]

The LDB data are compiled from administrative records and contain monthly recipiency information from the time that the case is first observed through to the end of 1992. Each person in the sample is followed throughout the sample period. If a person leaves welfare in 1990 then returns in 1992, both the earlier and later spell are observable.

This study uses a subset of the LDB: persons receiving AFDC. A code is provided for recipients to allow for the accurate identification of single-parent families with children (AFDC-FG, or family group recipients) and two-parent families with children (AFDC-UP, or unemployed parent recipients). Characteristics of the family that are contained in the data include the age, race/ethnicity, and gender of parent(s); the number, ages, and race/ethnicity of each of the children in the case; and the residential location. The ethnicity variable identifies white, black, Hispanic, Native Americans, Pacific Islanders, and eight Asian groups.[11]

These data are uniquely suited for this analysis for a number of reasons. First, the sample size is large, containing more than 15,000 AFDC cases (compared to 500–1,000 in the standard survey data sets). This large sample allows for the identification of important subgroups of recipients including two-parent families receiving AFDC-UP, and different racial/ethnic groups such as blacks, Hispanics, and southeast Asians. Second, the data contain information on the county and ZIP code of residence, allowing for identification of relatively small labor market areas.[12] Third, because the data are based on administrative data, the spells are measured accurately, without recall error.[13] The data allow for the identification of monthly participation in AFDC, while the PSID (the major data set used in this area) captures annual welfare spells. As is well known, given that eligibility for AFDC is determined on a monthly basis, the use of annual data can create significant measurement error, or time aggregation, problems.[14] Finally, data from California provide an excellent sample to use for this study. California contains approximately 15% of the nation's AFDC caseload, which is more than twice the size of the next largest state (U.S. House of Representatives, 1994). The period covered by the data set includes a period of economic expansion and falling unemployment rates (1987–1990) followed by a recession with rising unemployment rates (1990–1992).

The data set does have drawbacks, however. First, because it is based on administrative data, the demographic information for the recipients is limited. Second, the survey is a sample of Medi-Cal recipiency and not actual AFDC receipt. (If a woman starts receiving AFDC, but is never issued a Medi-Cal card, she would never appear in the sample.) This problem is not likely to be severe because AFDC recipients are categorically eligible for Medicaid and the participation rate among AFDC recipients is over 97% (U.S. House of Representatives, 1994).[15] Third, the LDB is a sample of recipients, consequently, we do not look at the

[9] Local labor markets have been found important in determinants of marriage among low-income women (Winkler, 1994), fertility (Duncan & Hoffman, 1990), youth unemployment (Acs & Wissoker, 1991; Cain & Finnie, 1990; Freeman, 1981), and labor market outcomes more generally (Bartik, 1991, 1996; Blanchard & Katz, 1992; Holzer, 1991; Hotz, et al., 1995). To the extent that these outcomes directly or indirectly affect welfare utilization, they provide suggestive evidence for a link between macroeconomic conditions and welfare.

[10] In addition to the 1% file, a 10% file is also available. Sample sizes based on the 10% file are upwards of 125,000 spells and 2,000,000 person-months (the unit of analysis for estimation). To avoid a heavy computational burden, this study uses the 1% file. A limited analysis of the 10% data shows virtually identical parameter estimates, but they are estimated with greater precision. Results are available upon request.

[11] While Hispanics can be of any race, separate race and ethnicity variables are not provided on the LDB.

[12] The public-use version of the data identifies counties with at least 100,000 residents and does not identify ZIP codes. Of the 58 counties in the state, 24 contain smaller populations and are identified as county groups. I was given access to a confidential file with a full set of county identifiers and the ZIP code data.

[13] There is some evidence of seaming in the LDB data. That is, a disproportionate number of spells end in December and, to a lesser extent, begin in January. California Department of Social Service analysts suggest that this is a result of county record-keeping procedures.

[14] The SIPP allows for monthly spells but it suffers from seaming problems (Blank & Ruggles, 1996) and a relatively short (28 month) survey period. The NLSY allows for monthly spells but is valid for only the young cohort that it covers. Since 1984, the PSID has collected monthly AFDC participation information. Both the PSID and NLSY monthly data are constructed retrospectively from annual interviews.

[15] Operationally "receiving Medi-Cal" means that the individual holds a Medi-Cal card. It is not necessary that they actually receive benefits, just that they are potentially able to do so. According to state welfare analysts, application for Medi-Cal usually is done at the same time application of AFDC is started.

determinants of initial entry into welfare. Lastly, people moving out of state are lost entirely and cannot be differentiated from people ending a welfare spell.[16]

The LDB data are used to examine the determinants of exits from welfare and reentry to welfare. The monthly information on welfare receipt is therefore used to construct welfare and non-welfare spells for each case in the sample. Welfare spells are the periods of continuous welfare receipt in which interruptions of one month are ignored.[17] Periods of nonreceipt begin in the month after the AFDC ends, and they end when a new AFDC spell begins. Both welfare and non-welfare spells can be right-censored if the spell is still ongoing in December of 1992, the end of the sample period. Among the 17,264 AFDC cases in the LDB sample are a total of 25,560 AFDC spells and 16,390 nonreceipt spells. The final sample is obtained after dropping all left-censored spells, "child-only" cases, cases with parents older than 54, and cases with missing or inconsistent data. Left-censored spells are dropped because it is not possible to determine how long the individual has been on welfare; therefore, duration effects cannot be controlled for in the model.[18] Parents over 54 were dropped because employment is less likely to be an option for them. After the sample selection, 12,117 AFDC spells and 11,481 non-welfare spells remain. Approximately 75% of the welfare spells are first (not left-censored) spells, and the remainder are repeat spells.[19]

Because these administrative data are new and somewhat untested, tables 1 and 2 and figure 1 present descriptive statistics to examine its consistency with other studies of welfare dynamics. Table 1 compares estimates of exit and reentry rates in the LDB data to recent studies using monthly data. The top panel of the table presents estimates of the percent of AFDC spells that are completed within six months, one year, or two years. The bottom panel presents estimates of the percent of previous welfare recipients that return to AFDC within six months, one year, or two years. These estimates show that the LDB data are fairly consistent with the other studies using monthly welfare participation data (Blank & Ruggles, 1996; Fitzgerald, 1995; Gritz & MaCurdy, 1992; Harris, 1993, 1996; Pavetti, 1993). More specifically, the LDB data show somewhat longer welfare spells. For example, 46% of spells in the California data are completed in one year, compared to approximately 50%–55% in the SIPP and NLSY. (This may be due to the relative generosity of California's AFDC program or differences in the composition of the AFDC population.) The LDB shows that, after leaving welfare, almost a quarter return within six months and one third return within one year, putting it in the middle of the range of estimates.

Figure 1a shows the empirical hazard rate for leaving welfare by month in the LDB sample. The circles indicate the estimate of the hazard rate, and the vertical lines indicate the 95% confidence interval around the estimate. After rising for the first few months, the hazard declines throughout the spell. Figure 1b shows that the risk of returning to welfare declines with length off welfare. These patterns are consistent with other studies.[20]

TABLE 1.—ESTIMATES OF EXITS FROM AND REENTRY TO AFDC
Comparison to Recent Studies Using Monthly Data

Studies of Exits from AFDC

Study	Data Set	Percentage of AFDC Spells Completed in: < = 6 Months	< = 12 Months	< = 24 Months
This study	California LDB 1987–1992	28%	46%	62%
Blank and Ruggles (1996)	SIPP 1986, 1987	—	55%	75%
Fitzgerald (1995)[1]	SIPP 1984, 1985	35%	52%	70%
Gritz and MaCurdy (1992)	NLSY 1979–1987	36%	55%	68%
Pavetti (1993)	NLSY 1979–1989	—	56%	70%
Harris (1993)	PSID 1984–1989 (monthly)	24%	44%	64%

Studies of Reentry to AFDC

Study	Data Set	Percentage of Previous Recipients Returning to AFDC in: < = 6 Months	< = 12 Months	< = 24 Months
This study	California LDB 1987–1992	23%	33%	41%
Gritz and MaCurdy (1992)	NLSY 1979–1987	21%	37%	49%
Pavetti (1993)	NLSY 1979–1989	—	45%	58%
Harris (1996)	PSID 1984–1989 (monthly)	14%	27%	42%

[1] The calculations from Fitzgerald measure the probability that the spell lasts ***less than*** each of the months shown in the table. All of the others measure the probability that the spell lasts ***less than or equal to*** each of the months shown.

[16] This feature of the data is expected to lead to a downward bias in the estimated labor market effects if recipients are more likely to move out of areas with poor labor markets. Out migration, however, is only a problem if the migrants continue to receive aid in the new state. A tabulation of the 1994 Current Population Survey shows that rates of out migration from California among poor single-parent families is very low.

[17] According to discussions with county welfare administrators, the majority of spell disruptions of one month are due to recipients' delay in submitting routine eligibility forms.

[18] Dropping left-censored spells may lead to an upward bias in the estimates, as the excluded spells are more likely to be longer and less sensitive to labor market conditions.

[19] Left-censored spells and "child-only" cases (no parent in the recipiency unit) account for most of the sample reduction. Among the welfare spells, 5,783 spells are left-censored and 4,670 spells are child-only. The remainder of the dropped observations come from omitting cases with older parents or missing/incorrect data (no children in case, miscoded race codes). By construction, there are no left-censored, non-welfare spells, so the sample reduction is smaller. Child-only cases are quite common in California, accounting for approximately 20% of all AFDC cases (California DSS, 1994). The most common reason for this is that the parent is an undocumented immigrant. Because these parents are not in the aid group, I do not have any information about them.

[20] As is well recognized in the literature, a decreasing hazard can be a result of true state dependence or unobserved heterogeneity. For example, those at risk of returning to welfare may be more likely to do so early; so the average risk of returning decreases as time off welfare increases.

FIGURE 1A.—NONPARAMETRIC HAZARD FOR PROBABILITY OF ENDING AFDC SPELL

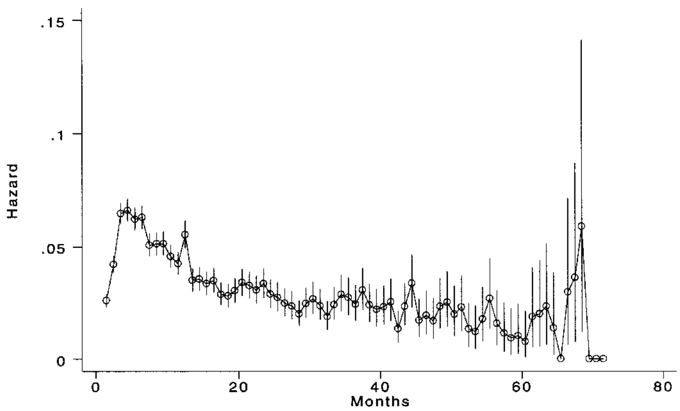


Table 2 expands on the analysis in table 1 by presenting estimates of length of welfare and non-welfare spells by demographic group using the LDB data. The table shows that single-parent families, younger parents, nonwhites, and families living in urban areas have longer welfare spells. The differences are particularly striking across racial groups: 31% of welfare spells end within six months for whites compared to 23% among blacks and 28% among Hispanics. Similarly, families headed by blacks, Hispanics, and teens are more likely to return to welfare. These differences across groups are statistically significant.

B. *Local Labor Market Variables*

The conceptual model of welfare participation, presented in section 2, suggests that we should introduce controls for both the availability of jobs and the potential returns from working. We present results for three measures for employment opportunities (unemployment rate, log of employment, and the employment-to-population ratio) and one measure of earnings opportunities. These data come from two sources. Employment and earnings data come from quarterly unemployment insurance (UI) reports known as 202 data. The 202 data are establishment data based on a large

FIGURE 1B.—NONPARAMETRIC HAZARD FOR PROBABILITY OF RETURNING TO AFDC

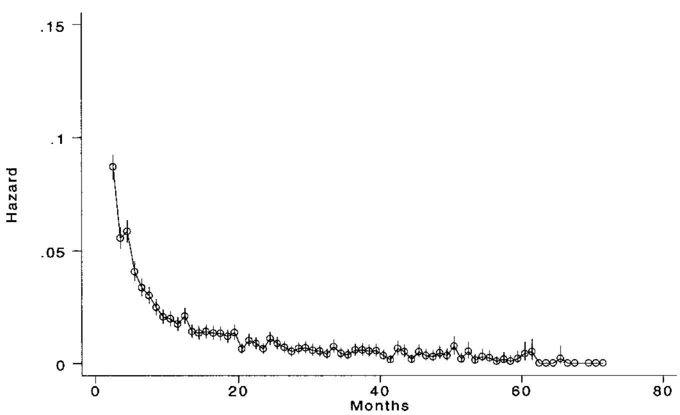


TABLE 2.—DISTRIBUTION OF LENGTH OF AFDC AND NON-AFDC SPELLS BY DEMOGRAPHIC GROUP, UNCONDITIONAL ESTIMATES

		Probability that an AFDC Spell is Completed in:			
	Number of Spells	< = 6 Months	< = 1 Year	< = 2 Years	< = 4 Years
All	12,177	0.28	0.46	0.62	0.75
Single-parent (AFDC-FG)	10,313	0.27	0.45	0.62	0.75
Two-parent (AFDC-UP)	1,864	0.31	0.48	0.63	0.72
White	5,835	0.31	0.51	0.67	0.79
Hispanic	2,855	0.28	0.45	0.61	0.74
Black	2,639	0.23	0.41	0.57	0.70
Asian refugee groups	458	0.10	0.19	0.31	0.43
Other	390	0.24	0.42	0.62	0.78
Non-teen head	11,081	0.28	0.47	0.63	0.76
Teen head	1,096	0.20	0.37	0.51	0.67
Urban	10,606	0.27	0.45	0.60	0.74
Non-urban	1,571	0.33	0.54	0.71	0.82
		Probability that a Previous AFDC Recipient Returns to AFDC in:			
	Number of Spells	< = 6 Months	< = 1 Year	< = 2 Years	< = 4 Years
All	11,481	0.23	0.33	0.41	0.46
Single-parent (AFDC-FG)	9,847	0.24	0.33	0.41	0.48
Two-parent (AFDC-UP)	1,634	0.21	0.33	0.41	0.47
White	5,620	0.22	0.32	0.39	0.45
Hispanic	2,636	0.24	0.35	0.43	0.49
Black	2,500	0.28	0.38	0.46	0.51
Asian refugee groups	269	0.18	0.23	0.27	0.31
Other	420	0.15	0.21	0.27	0.31
Non-teen head	10,745	0.23	0.32	0.40	0.45
Teen head	736	0.34	0.46	0.55	0.59
Urban	9,909	0.24	0.33	0.41	0.46
Non-urban	1,572	0.24	0.34	0.43	0.48

Source: Author's tabulation of LDB 1% case file.

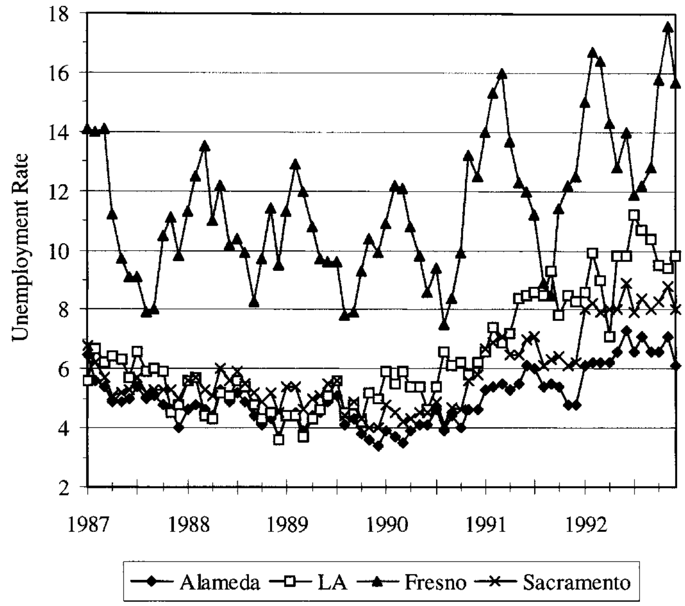
sample of employers in various industries, and it provides quarterly county employment and earnings figures by one-digit SIC code. These data are used to construct a time series of county-level employment (total and by sector), average earnings (total and by sector), and employment-to-population ratios. Average quarterly earnings are constructed by dividing total quarterly payroll by quarterly employment. This is not a wage measure and instead reflects expected earnings conditional on obtaining a job; it also varies with turnover and hours worked. Employment-to-population ratios (or employment rates) use annual county population figures, which are interpolated between decennial census years. The second data source is monthly county unemployment rates, available from the California Labor Market Information Division.

The establishment-level data are preferred for two reasons. First, unemployment rates at the county level are generally thought to be estimated with more measurement error than employment. Employment is relatively easy to enumerate with surveys of employers, while unemployment rates require household surveys. Most counties are too small to be separately identified even in large household surveys such as the Current Population Survey (CPS). In fact, Los Angeles is the only county in California with a population large enough to be identified in the CPS. Consequently, county unemployment rates are imputed using the "handbook method" (U.S. Bureau of Labor Statistics, 1992), which relies on many data sources and has been criticized for generating data with significant measurement error (Bartik, 1996). This could be particularly troublesome when the estimates are identified using cross-county differences in the trends of labor market conditions, as is the case when county and time effects are included. Second, unemployment rates are less desirable measures of labor market opportunities because they fluctuate not only with employment but also with changes in labor force participation.

We observe county of residence for each month on welfare, and the labor market variables are assigned to each recipient in each month they are on welfare based on their county of residence.

Critical to the study is sufficient variation in labor market conditions both across areas and over time. California has significant variation in labor market conditions. Figure 2 shows unemployment rates by county for a few large and illustrative counties. Los Angeles county accounts for approximately 35% of the state's total AFDC caseload, while the other counties represented in the graph each account for 5%–8% of the state caseload. The 1990 recession hit sooner and harder in southern California, and unemployment rates in the northern urban areas are generally lower than those found in the south throughout the period. Fresno county is an important agricultural county in the state, and it has the largest AFDC caseload outside the major urban areas. Unemployment is much higher and more seasonal, reflecting the importance of the agricultural sector. Employment rates show similar patterns.

FIGURE 2.—UNEMPLOYMENT RATES FOR SELECTED CALIFORNIA COUNTIES, 1987–1992



C. *Neighborhood Variables and Other Variables*

Because of limited demographic variables, the LDB data are augmented by controlling for the characteristics of the neighborhood in which the family resides using 1990 Census ZIP code-level summary files.[21] These effects are assumed to be constant throughout the spell because they are measured at a single point in time. The variables included are median household income, percent of women never married, and urban designation.[22]

Resources spent on job training and education may vary significantly across counties. Accordingly, the empirical work also includes measures of participation and cost of the Greater Avenues for Independence (GAIN) program. California's GAIN program, the nation's first and largest welfare-to-work program, stresses education, basic skills, training, and job search. The GAIN data are available annually and are used to construct two variables: county GAIN participation rate and expenditures per GAIN participant.[23]

V. Empirical Model

The determinants of welfare exits and reentry are estimated using a discrete time hazard model (Kalbfleisch & Prentice, 1980; Lancaster, 1990). Beginning with a general model, the basic element of a duration model is the hazard rate or transition probability, $\boldsymbol{P(t, Z)}$, which captures the probability of leaving a state in the t^{th} period given continuous participation in that state for the last $\boldsymbol{t}$**-1** periods and covariates $\boldsymbol{Z}$. Using the hazard rate, we can construct the duration distribution $\boldsymbol{f(t, Z)}$ (the probability that an individual experiences a spell of length $\boldsymbol{t}$) and the survivor function $\boldsymbol{F(t, Z)}$ (the probability that an individual will experience a spell of at least $\boldsymbol{t}$ periods).[24] Both distributions are conditional on covariates $\boldsymbol{Z}$ and on initial entry into the state. Given a specification for the transition probability and covariates $\boldsymbol{Z}$, the parameters of the model are estimated using conventional maximum-likelihood methods. An uncensored spell of length $\boldsymbol{T}$ contributes $\boldsymbol{f(T, Z)}$ to the likelihood

[21] ZIP codes represent a relatively small geographic area. While census tracts contain approximately 4,000 to 5,000 persons, ZIP code areas in California average approximately ten to twenty times the size of a census tract. They are smaller than PUMAs, which contain at least 100,000 persons, and MSAs. A total of 1,106 ZIP codes is represented in the data, or about 26 per county.

[22] Other variables examined include rates of poverty, high-school completion, and employment. In practice, these variables were found to be highly collinear, and only a subset are used in the estimates.

[23] Studies of welfare participation typically control for AFDC benefit levels. In this analysis, benefits vary only over time, and this effect will be captured by the unrestricted time effects.

[24] Dropping the covariate vector $\boldsymbol{Z}$ for simplicity, the hazard rate, duration distribution, and survivor function are linked by $\boldsymbol{f(t)} = \boldsymbol{S(t-1)} \times \boldsymbol{P(t)}$ and $\boldsymbol{S(t)} = \Pi_{\tau=1}^{t}[1 - \boldsymbol{P(\tau - 1)}]$.

function, and a right-censored spell of length T contributes $F(T, Z)$ to the likelihood function.

In this application, the covariate vector Z varies by individual i, living in county c, in time t. The hazard rate $P(t, Z_{ict})$ is modeled as a logit probability:

$$P(t, Z_{ict}) = \frac{\exp(\alpha_t + Z_{ict}\Pi)}{1 + \exp(\alpha_t + Z_{ict}\Pi)}. \tag{1}$$

The logit specification has been used often in the literature (Bane & Ellwood, 1983; Blank & Ruggles, 1996; Ellwood, 1986; Fitzgerald, 1994, 1995; Harris, 1993, 1996; Hoynes & MaCurdy, 1994) and is attractive because it allows for time-varying covariates and a flexible form for the effect of time in the spell on exits. The α_t are dummy variables for length of the spell to date, and they nonparametrically account for the basic duration properties of the model. These duration effects create a baseline hazard, and the covariates Z_{ict} scale the exit probabilities up or down uniformly. The Z_{ict}'s are specified as

$$\begin{aligned} Z_{ict}\Pi = {} & X_i'\beta + L_{ct}'\delta + \gamma_0 \text{County}_{ct} \\ & + \gamma_1 \text{Time}_t + \gamma_2 \text{County}_{ct} * \text{Trend}_t \end{aligned} \tag{2}$$

and contains controls for demographic characteristics (X_i), county-level time varying labor market variables (L_{ct}), county fixed effects, time effects, and county time trends. With these additional area and time controls, the labor market effects will be identified off of differences in trends in labor markets across areas (or differences in deviations from trends with the county-specific time trend). This purges the model of any omitted county-level or trend effects that may bias the estimated labor market effects.[25]

This model is applied to the estimation of both exits from welfare and returns to welfare. For the exit model, the dependent variable equals 1 when the family leaves welfare, and the duration variables control for the length of time on welfare to date. In the reentry model, the dependent variable equals 1 if the family transitions back onto welfare, and the duration variables control for length of time since the last welfare spell ended.[26] These two outcomes are estimated independently. In practice, a single family may have multiple (welfare and/or non-welfare) spells. These spells are assumed to be independent.[27]

The local labor market variables must be exogenous in order to obtain unbiased estimates of the parameters of interest. A potential source of endogeneity is if persons with low education levels and poor employment prospects were more likely to be located in areas with adverse economic conditions. Another possibility is that areas with good economic conditions provide more job placement services for welfare recipients. If these unmeasured attributes are fixed over time, then controlling for county-level fixed effects and the neighborhood variables will take care of the endogeneity. If, however, selective migration takes place during the welfare spell in response to labor market conditions, the results will be biased. To handle this possibility, an extension to the main results replaces current county with the family's county of residence at the beginning of the spell.[28]

The issue of endogenous migration is related to the more general issue of unobserved heterogeneity. It is well known that the presence of unobserved heterogeneity can affect the interpretation of the duration effects. (A declining hazard can be due to true state dependence or a difference in the composition of the population as it becomes more composed of long-time users.) In addition, if people differ in their underlying propensity to utilize welfare and this propensity is correlated with observable demographic variables, then the interpretation of these variables becomes unclear.

VI. Results

In this section, we present the results for discrete duration models of exit from AFDC and reentry back into AFDC. The sample for estimating AFDC exits consists of 191,294 observations, with one observation for each month in the welfare spell. The sample for estimating returns to AFDC consists of 253,392 observations, with one observation for each month in the non-welfare spell. Table 3 presents descriptive statistics for the two estimation data sets. The demographic variables (X_i) include dummies for age and race/ethnicity of the parent, the number of children (KIDS), dummies for age of the youngest child, whether an adult male is present (MALE), and whether the family is an AFDC-UP recipient (AFDCU). The variable PREG is equal to 1 if the woman is pregnant with no other children in the household at the beginning of the spell. The county labor market variables (L_{ct}) include the unemployment rate URATE, the log of employment LN(E), the employment-to-population ratio E/POP, and average quarterly earnings EARN. Studies have shown that previous welfare recipients are disproportionately working in the retail trade and service

[25] As explained below, the demographic characteristics X are not time varying and are fixed as of the beginning of the spell.

[26] The LDB data contain information for only the months that an individual is on aid. Consequently, for the analysis of returns to welfare, we assume that the county of residence and individual characteristics are held constant at their value as of the last month of the last welfare spell.

[27] Descriptive evidence suggests that these independence assumptions may not be valid, as those with long spells are more likely to return to welfare (Ellwood, 1986; Harris, 1996). Estimating a fully integrated model would increase the efficiency of the results. In this study, the independence assumption may not be a problem, because estimates of the exit model on a sample limited to one spell per family yields very similar results to those presented here.

[28] A problem remains if migration takes place prior to welfare entry, but there are systematic changes in this migration over time. Perhaps there is an increase in poor immigrants flowing into a particular labor market over time. In short, if the unobserved county characteristics are changing over time, then controlling for county-fixed effects will not correct the problem. The available evidence suggests that this is not likely to be a problem, as welfare recipients do not seem to migrate in response to the incentives (Moffitt, 1992; Walker, 1994).

TABLE 3.—DESCRIPTIVE STATISTICS FOR ESTIMATION SAMPLES

Variable	Definition	*Exit Sample* Mean	*Exit Sample* Standard Deviation	*Reentry Sample* Mean	*Reentry Sample* Standard Deviation
Demographics					
TEEN	head < 20	0.09		0.04	
AGE24	head 20–24	0.23		0.20	
AGE34	head 25–34	0.44		0.45	
AGE44	head 35–44	0.20		0.24	
AGE54	head 45–54	0.05		0.07	
WHITE	head is white	0.48		0.48	
HISP	head is Hispanic	0.23		0.23	
BLACK	head is black	0.22		0.21	
FILIP	head is Filipino	0.01		0.006	
CAMB	head is Cambodian	0.01		0.002	
LAOT	head is Laotian	0.01		0.003	
VIET	head is Vietnamese	0.02		0.014	
OTHER	head is other race	0.03		0.048	
KIDS	number of kids	1.65	1.11	1.74	1.06
PREG	woman is pregnant with no other kids	0.09		0.04	
YCH2	youngest child < = 2	0.38		0.36	
YCH5	youngest child 3–5	0.21		0.24	
YCH6	youngest child 6 or more	0.31		0.40	
MALE	male head	0.03		0.05	
AFDCU	case participating in AFDC-UP	0.15		0.14	
Labor Market Variables					
URATE	unemployment rate, monthly	7.46	3.33	7.56	3.33
EARN	avg quarterly earnings, all indus (1000s)	6.699	1.085	6.708	1.123
EARNSE	avg quarterly earnings, services (1000s)	6.585	1.046	6.585	1.071
EARNRE	avg quarterly earnings, retail trade (1000s)	3.920	0.408	3.913	0.413
LN(E)	log of employment, quarterly	13.23	1.59	13.23	1.59
LN(SE)	log of service employment, quarterly	12.19	1.61	12.10	1.67
LN(RE)	log of retail trade employment, quarterly	11.55	1.48	11.47	1.52
E/POP	employment to population ratio, quarterly	0.40	0.09	0.40	0.09
Neighborhood Variables and Other County Vars					
URB-I	urban, inside urbanized area	0.86		0.82	
URB-O	urban, outside urbanized area	0.10		0.09	
RUR	rural	0.04		0.09	
MINC	household median income (1000s)	30.743	9.418	30.181	9.610
%NVMAR	% of women never married	0.25	0.07	0.25	0.07
GAIN%	GAIN Partic/AFDC Recip, annual	0.14	0.10	0.14	0.11
GAIN$	GAIN Exp/GAIN Partic (1000s), annual	2.16	1.45	2.23	1.42
Number of observations		191,294		253,392	

Source: Author's tabulations of LDB 1% case file. The data set contains one observation for each monthly transition in the welfare and non-welfare spells data. Because of a small number of missing ZIP codes, neighborhood variables are available for only 181,728 observations in the exit sample and 236,566 in the reentry sample.

sectors (Brandon, 1995), so we also consider controls for average earnings and log employment in retail trade (EARNRE, LN(RE)) and services (EARNSE, LN(SE)). The neighborhood characteristics and GAIN variables are summarized at the bottom of the table. Urban residents can consist of those who live within an "urbanized area" (URB-I) and those living in urban areas outside an "urbanized area" (URB-O) or rural areas (RUR).[29] The vast majority of recipients live in urbanized areas, while only 4% reside in rural areas. Median household income (MINC) averages $30,743 and, on average, 25% of women over 18 in the ZIP code area have never been married (%NVMAR).[30]

[29] The Census bureau's definition of ***urban*** includes both urbanized areas and parts of non-urbanized areas. An urbanized area is one with 50,000 or more persons. Places with more than 2,500 persons that are not part of urbanized areas are also considered urban.

[30] A small fraction of the cases do not have valid ZIP codes. Dropping observations without valid ZIP codes reduces the exit sample to 181,728 from 191,294 and reduces the reentry sample to 236,566 from 253,392. Estimates of labor market effects on the full sample (not shown here) show virtually identical results to those estimated on the sample with valid ZIP codes.

A. *Preliminary Estimates without Labor Market Variables*

Table 4 presents estimates from the discrete duration model before adding any labor market variables. For modeling exits from welfare, the dependent variable is equal to 1 if the welfare spell ends, and a positive coefficient implies that an increase in the covariate leads to higher exit rates (and shorter welfare spells). For modeling returns to welfare, the dependent variable equals 1 if the non-welfare spell ends in a return to welfare, and a positive coefficient implies that an increase in the covariate leads to higher reentry rates (and shorter spells off welfare). The basic specification includes controls for demographics (age, race, and gender of parent; number and ages of children; and AFDC program type), neighborhood variables (median household income, percent of women never married, urban status), GAIN variables, and

TABLE 4.—PARAMETER ESTIMATES FOR BASIC MODELS, *No Labor Market Variables*

	Change in Variable	*Exits from Welfare* Estimate	*Exits from Welfare* % Change in 1-year Exit Rate	*Reentry to Welfare* Estimate	*Reentry to Welfare* % Change in 1-year Reentry Rate
AGE24	0 to 1	0.174***	12.1%	− 0.204***	− 15.6%
AGE34	0 to 1	0.149***	10.3%	− 0.365***	− 26.5%
AGE44	0 to 1	0.205***	14.3%	− 0.747***	− 47.7%
AGE54	0 to 1	0.087	6.0%	− 0.984***	− 59.9%
HISP	0 to 1	− 0.042	− 2.8%	0.160***	13.7%
BLACK	0 to 1	− 0.148***	− 9.9%	0.302***	27.0%
FILIP	0 to 1	− 0.107	− 8.4%	0.021	1.8%
CAMB	0 to 1	− 1.188***	− 61.4%	− 0.201	− 15.4%
LAOT	0 to 1	− 1.086***	− 57.8%	− 0.271	− 20.3%
VIET	0 to 1	− 1.369***	− 67.2%	− 0.528***	− 36.3%
OTHER	0 to 1	− 0.126	− 7.1%	− 0.425***	− 30.3%
KIDS	1 to 2	− 0.056***	− 3.8%	0.042**	3.5%
PREG	0 to 1	− 0.345***	− 22.1%	0.218***	19.0%
YCH5	0 to 1	0.032	2.2%	− 0.068*	− 5.4%
YCH6	0 to 1	0.148***	10.3%	− 0.074	− 5.9%
MALE	0 to 1	0.343***	24.2%	0.592***	56.2%
AFDCU	0 to 1	0.110***	7.6%	0.133***	11.3%
URB-I	0 to 1	− 0.176***	− 11.7%	− 0.036	− 2.9%
URB-O	0 to 1	− 0.090	− 6.0%	− 0.069	− 5.5%
MINC	30.7 to 36.9 (+20%)	0.006***	2.7%	− 0.006***	− 2.9%
%NVMAR	0.25 to 0.32	− 0.686***	− 3.2%	− 0.828***	− 4.7%
GAIN$	$2.2 to $2.6 (+20%)	− 0.022**	− 0.7%	− 0.026**	− 0.2%
GAIN%	0.14 to 0.24	0.208*	1.4%	− 0.019	− 3.1%
Constant		− 5.941**		− 2.428***	
N		181,728		236,645	
LogL		− 30,176		− 20,707	

Notes: Estimates are based on a logistic model in which the dependent variable equals 1 for a welfare exit (column 1) or welfare reentry (column 2). Each specification also includes dummies for duration of spell. Asterisks indicate that the coefficient is significantly different from zero at the 10% (*), 5% (**), and 1% (***) level. The baseline exit rate is 0.46, and the reentry rate is 0.30 and is set for a white, single mother aged <20 with one child <3, living in a rural area. All other variables are set to their mean values.

duration effects. This simple specification does not control for county or time effects. The demographic variables are set as of the beginning of the spell and are not time-varying.[31] In these and all subsequent specifications, the duration dummies consist of single-month dummies for the first twelve months, three-month dummies for the next two years, and six-month dummies for the last three years. The duration parameters are suppressed from the table of estimates.

The parameter estimates show that black and Hispanic families, and families with younger parents, more children, and younger children are more likely to be participating in welfare, through both longer welfare spells and shorter periods off welfare. To assess the economic importance of the variables, the table presents simulations of the effects of changes in each of the variables on the one-year exit (or reentry) rate. The first column of the table shows the change in the variable used for the simulation. For example, blacks are approximately 10% less likely to leave welfare within a year and 27% more likely to return within a year (conditional on leaving). Women beginning a spell with a first pregnancy are 22% less likely to complete a spell in one year and 19% more likely to return within a year of leaving welfare, compared to a woman with a child under age two. There is evidence that two-parent families and single-parent, male-headed families may cycle on and off welfare as they tend to have shorter welfare spells but also higher rates of return to welfare. The neighborhood variables significantly affect exits from welfare. Specifically, persons living in urban areas, with lower median household income, and with more never-married women have longer AFDC spells. The GAIN program appears to have very small effects.[32]

B. *Estimates of Local Labor Market Effects*

The main results with the local labor market variables are presented in table 5, 6, and 7.[33] Quarterly earnings are included in all specifications, and the tables differ only in their specification of the employment variable. Table 7 uses the unemployment rate, table 8 the log of employment, and table 9 the employment-to-population ratio. Increases in employment opportunities (lower unemployment rates and

[31] Among the limited characteristics available in the LDB data, only the number and ages of children vary over the spell. To minimize the potential endogeneity of fertility outcomes, these variables are fixed as of the beginning of the spell.

[32] Cambodians, Laotians, and Vietnamese are found to have dramatically longer welfare spells than any other racial group. At the time of this sample, most AFDC recipients from these countries are recent immigrants with current or previous refugee status. The groups are generally thought to have longer spells than native-born individuals due to limited English proficiency and poor labor market skills. Upon arrival to the United States, refugees are immediately enrolled in public assistance programs, and the conditions to maintain eligibility are more lenient than with other AFDC participants. This may also contribute to their longer spells. California has a large number of refugees relative to other states. The main results of the paper hold when persons in these racial groups are dropped from the sample.

[33] These and all subsequent tables suppress all covariates except the labor market variables. The full set of estimates is available from the author.

TABLE 5.—PARAMETER ESTIMATES FOR MODELS USING COUNTY UNEMPLOYMENT RATE

	(1)	(2)	(3)	(4)	(5)	(6)
Panel** A: **Parameter Estimates for Exits from Welfare						
URATE	−0.032***	−0.039***	−0.006	−0.015	−0.009	0.010
	(0.006)	(0.009)	(0.012)	(0.012)	(0.012)	(0.013)
EARN	−0.027	0.269***	0.237***	0.253***		
	(0.025)	(0.084)	(0.086)	(0.089)		
EARNSE					0.166***	
					(0.063)	
EARNRE						0.067
						(0.163)
Number of observations	181,728	181,728	181,728	181,728	181,728	181,728
Log likelihood	−30162	−30056	−30014	−29967	−29966	−29981
Panel** B: **Parameter Estimates for Reentry to Welfare						
URATE	0.006	0.016	0.012	0.017	0.013	0.014
	(0.007)	(0.011)	(0.020)	(0.024)	(0.026)	(0.026)
EARN	−0.017	−0.263	−0.137	−0.223		
	(0.029)	(0.211)	(0.176)	(0.195)		
EARNSE					−0.172	
					(0.110)	
EARNRE						0.066
						(0.300)
Number of observations	236,566	236,566	236,566	236,566	236,566	236,566
Log likelihood	−20520	−20490	−20453	−20424	−20422	−20426
Duration dummies	yes	yes	yes	yes	yes	yes
County fixed effects		yes	yes	yes	yes	yes
Time effects			yes	yes	yes	yes
County time trend				yes	yes	yes

Notes: Estimates are based on a logistic model in which the dependent variable equals 1 for a welfare exit (Panel A) or welfare reentry (Panel B). Each specification also includes individual and family characteristics, GAIN variables, and neighborhood variables. Standard errors, given in parentheses, are adjusted for the grouped nature of the labor market variables. Asterisks indicate that the coefficient is significantly different from zero at the 10% (*), 5% (**), and 1% (***) level.

higher employment, or employment-to-population ratios) and increases in returns to working (higher quarterly earnings) are expected to lead to higher exit rates and lower reentry rates. The structure of each of the three main tables is identical. The top panel of the table provides estimates of the exit rate, and the lower panel provides estimates of the reentry rate. Column (1) contains no county or time effects, column (2) adds county effects, column (3) adds time effects, column (4) adds county-specific linear time trends, and columns (5) and (6) use variables for service and retail trade sectors, respectively. All standard errors are adjusted for the grouped nature of the labor market variables.[34,35]

We begin with the unemployment rate because it has been used extensively in the literature. Column (1) in table 5 presents estimates without county or time effects. The estimates show that higher unemployment rates lead to lower exit rates and longer welfare spells. This finding contrasts with many studies that examine similar models but that use labor market variables at the state level. These results suggest that using a more localized measure of labor market opportunities (such as county) may be important for obtaining the theoretically expected effects. Specification (2) controls for the unobserved differences between the counties with county-fixed effects. This changes the coefficient on average earnings from negative and statistically insignificant to positive and significant and increases the magnitude of the unemployment effect by approximately 20%. Thus, in contrast to the results in Fitzgerald (1994), adding the county-fixed effects makes the results stronger.

The third specification in table 5 adds period dummies to the model. The danger is that there may be factors (such as increases in the minimum wage and reductions in AFDC benefits) that simultaneously affect all counties in the state that may also be correlated with state trends in labor market conditions and welfare utilization. This has little impact on the earnings estimate but renders the unemployment rate small and insignificant. This result has two possible explanations. The first is that the unemployment rate is measured with error. Given the census methodology for imputing county unemployment rates, controlling for fixed county and statewide time effects capture all of the useful variation. The second is that the trends in local labor market conditions do not vary enough across the counties to separately identify county, time, and labor market effects. As we will see, the former explanation appears to be the likely one as the estimates based on employment are robust to including time effects. Lastly, in equation (4), we add county-specific linear time trends to control for the possibility that area labor

[34] Specifically, the labor market variables do not vary within county and month (or quarter). The standard errors are corrected using the method in Huber (1967). This correction increases the standard errors on the labor market variables by between 20% and 50%.

[35] The standard errors are calculated assuming independence across spells for a given family. If the sample is limited to one spell per family, the standard errors increase by approximately 12%–15%, but the overall results are very similar to those reported here. Approximately 25% of the sample consists of a second or later spell, and the sample contains, on average, 1.3 welfare spells per case and 1.4 non-welfare spells per case.

TABLE 6.—PARAMETER ESTIMATES FOR MODELS USING COUNTY LOG EMPLOYMENT

	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A*: Parameter Estimates for Exits from Welfare*			
LN(E)	− 0.085***	1.225***	1.079***	2.179***		
	(0.018)	(0.418)	(0.374)	(0.641)		
LN(SE)					1.095***	
					(0.354)	
LN(RE)						0.846
						(0.555)
EARN	0.077***	0.235***	0.234***	0.209***	0.184***	0.231***
	(0.024)	(0.077)	(0.067)	(0.065)	(0.068)	(0.066)
Number of observations	181,728	181,728	181,728	181,728	181,728	181,728
Log likelihood	− 30166	− 30066	− 30009	− 29962	− 29964	− 29967
			Panel B*: Parameter Estimates for Reentry to Welfare*			
LN(E)	0.023	− 0.749	− 0.906	− 1.900**		
	(0.035)	(0.529)	(0.583)	(0.940)		
LN(SE)	− 0.044	− 0.246	− 0.146	− 0.201	− 0.608	
	(0.037)	(0.182)	(0.150)	(0.165)	(0.665)	
LN(RE)						− 1.817**
						(0.795)
EARN					− 0.219**	− 0.204
					(0.168)	(0.162)
Number of observations	236,566	236,566	236,566	236,566	236,566	236,566
Log likelihood	− 20519	− 20490	− 20451	− 20422	− 20424	− 20421
Duration dummies	yes	yes	yes	yes	yes	yes
County fixed effects		yes	yes	yes	yes	yes
Time effects			yes	yes	yes	yes
County time trend				yes	yes	yes

Notes: Estimates are based on a logistic model in which the dependent variable equals 1 for a welfare exit (Panel A) or welfare reentry (Panel B). Each specification also includes individual and family characteristics, GAIN variables, and neighborhood variables. Standard errors, given in parentheses, are adjusted for the grouped nature of the labor market variables. Asterisks indicate that the coefficient is significantly different from zero at the 10% (*), 5% (**), and 1% (***) level.

market conditions and welfare participation may be trending up or down, but for unrelated reasons. The identification then comes from differences in the deviations around county trends. Although this increases the estimates on the labor market variables somewhat, it does not substantively change the results.

The remaining columns of table 5 replace average earnings by average earnings in services (specification (5)) and average earnings in retail trade (specification (6)). These results show that service-sector earnings significantly affect exits from welfare, but earnings in retail trade are surprisingly not statistically significant. This result is quite robust, holding for alternative controls for job availability and in the absence of the period effects. An analysis of variance shows that retail earnings vary less over time than service earnings, which may explain this result. As we will see, retail-sector employment growth is important.

Similar patterns are found in the analysis of reentry, presented in panel (B) of table 5. Increases in unemployment rates and decreases in earnings are associated with higher recidivism rates. As with exits, controlling for local area-fixed effects is important, especially in the case of earnings. The results for reentry, while qualitatively similar to the results for exits, are less precisely estimated. The recidivism results, however, are somewhat sensitive to sample selection. If we drop non-welfare spells that last only two months (reducing the sample size by approximately 1%), the estimates for the labor market variables increase in magnitude by approximately 50% and are generally statistically significant. This pattern is also found in the specifications based on employment and employment-to-population ratios. The justification for dropping short non-welfare spells is that they may not be real spells. (For example, they may be explained by administrative factors.)

Table 6 presents estimates that replace the unemployment rate with the log of county employment. Column (1) presents estimates without county-fixed effects. These results show an unexpected positive relationship between employment and length of welfare spell. This, however, seems to be capturing unobserved differences across counties, which are correlated with welfare participation. Controlling for county-fixed effects (column 2) shows that higher employment and earnings growth lead to shorter spells on welfare and lower rates of return to welfare. In contrast to the estimates in table 5, the results are only strengthened by adding statewide period effects (column (3)) and county-specific time trends (column (4)). In particular, adding the county time trends increases the estimates on employment significantly, suggesting that counties that are trending up in employment are also trending up in welfare participation. The last two columns of table 6 replace the log of county employment with the log of service employment (specification 5) and retail trade employment (specification (6)). These results show that higher growth in retail trade and service

TABLE 7.—PARAMETER ESTIMATES FOR MODELS USING COUNTY EMPLOYMENT-TO-POPULATION RATIO

	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A*: Parameter Estimates for Exits from Welfare*			
E/POP	0.637***	5.115***	2.509**	3.458***	2.511**	2.989***
	(0.232)	(0.856)	(1.111)	(1.266)	(1.211)	(1.370)
EARN	−0.024	0.294***	0.254***	0.261***		
	(0.027)	(0.072)	(0.069)	(0.068)		
EARNSE					0.160***	
					(0.041)	
EARNRE						0.068
						(0.156)
Number of observations	181,728	181,728	181,728	181,728	181,728	181,728
Log likelihood	−30183	−30038	−30011	−29963	−29963	−29977
			Panel B*: Parameter Estimates for Reentry to Welfare*			
E/POP	−0.099	−1.986	−2.671*	−2.486	−1.681	−1.907
	(0.314)	(1.394)	(1.458)	(1.792)	(1.919)	(1.880)
EARN	−0.019	−0.288	−0.168	−0.239		
	(0.029)	(0.199)	(0.152)	(0.163)		
EARNSE					−0.170*	
					(0.090)	
EARNRE						−0.019
						(0.221)
Number of observations	236,566	236,566	236,566	236,566	236,566	236,566
Log likelihood	−20520	−20489	−20451	−20423	−20421	−20426
Duration dummies	yes	yes	yes	yes	yes	yes
County fixed effects		yes	yes	yes	yes	yes
Time effects			yes	yes	yes	yes
County time trend				yes	yes	yes

Notes: Estimates are based on a logistic model in which the dependent variable equals 1 for a welfare exit (Panel A) or welfare reentry (Panel B). Each specification also includes individual and family characteristics, GAIN variables, and neighborhood variables. Standard errors, given in parentheses, are adjusted for the grouped nature of the labor market variables. Asterisks indicate that the coefficient is significantly different from zero at the 10% (*), 5% (**), and 1% (***) level.

employment lead to shorter spells on welfare and lower rates of return to welfare.[36]

The final measure of job availability is the employment-to-population ratio. The results, presented in table 7, are qualitatively very similar to log employment regressions. Controlling for permanent cross-area differences is important for obtaining the theoretically expected effects of labor markets. Adding statewide time effects and county-level time trends changes the estimates somewhat, but the main results still hold: higher earnings and employment-to-population ratios are associated with significantly shorter spells on welfare and longer periods off welfare. The results in the last two columns show, consistent with the results in table 5, that service-sector earnings growth (but not retail trade earnings growth) is associated with lower welfare participation (quicker exits and slower reentry). In general, it is striking how consistent the estimates are for the earnings variables across the different specifications shown in these three tables.

C. *Assessing the Importance of Labor Market Effects*

Tables 8 and 9 present simulations of the effects of changes in labor market variables on changes in the probability of exiting welfare (table 8) and returning to welfare (table 9). As with the earlier simulations (table 4), the figures in the table show the percentage change (relative to the baseline specification) in the probability that a welfare spell is completed within one year (in the case of exits) or the probability that a previous recipient returns to welfare within one year (in the case of reentry) that results from a given change in the labor market variable. Each row in the table represents the results of a different specification from tables 5, 6, and 7. The simulations are based on a reduction in unemployment rates of three percentage points, a 10% increase in employment, a reduction in the employment-to-population ratio of 3.5 percentage points, and a 5% increase in earnings. Each of these simulated changes in the labor market variables represent typical within-county changes in the variables observed over the 1987–1992 period and can be interpreted as the variation that we might expect between the trough and peak of a business cycle. The specifications using the unemployment rate are included for completeness, but the discussion will be based on the regressions using the log of employment and the employment-to-population ratios.

The simulations in table 8 show large and remarkably consistent effects of employment and earnings on exits from welfare. Depending on the specification, a 5% increase in real quarterly earnings leads to a 4.8%–6.8% increase in the probability that a spell is completed within one year. The simulations using employment show somewhat larger and

[36] Note that adding employment growth directly in the regression, with or without county-fixed effects, shows very similar results to those presented here.

TABLE 8.—PREDICTED EFFECT OF CHANGES IN LOCAL LABOR MARKETS ON EXIT RATES
PERCENTAGE CHANGE IN THE PROBABILITY THAT AN AFDC SPELL ENDS WITHIN ONE YEAR

	Specification	URATE 7.5% to 4.5% (−3 p.p)	LN(E) 13.2 to 13.3 (Emp +10%)	E/POP 0.40 to 0.435 (+3.5 p.p)	EARN 6.7 to 7.0 (+5%)
Unemployment Rates Models					
County effects	Table 5(2)	8.1%			6.1%
County, time effects	Table 5(3)	1.2%			5.6%
County, time, county trend	Table 5(4)	3.0%			5.8%
Log Employment Models					
County effects	Table 6(2)		8.6%		5.5%
County, time effects	Table 6(3)		7.3%		5.3%
County, time, county trend	Table 6(4)		15.4%		4.8%
Employment/Population Models					
County effects	Table 7(2)			12.5%	6.8%
County, time effects	Table 7(3)			6.1%	5.9%
County, time, county trend	Table 7(4)			8.3%	6.0%

Notes: Each row represents the simulations based on a particular specification of the exit model. The figures represent the percentage change in the predicted probability that the welfare spell lasts one year or less (relative to a baseline) resulting from a given change in each of the local labor market variables. The first two columns describe which model is being simulated. The baseline probability is 0.50, which is calculated for a white, single mother aged 25–34 with one child younger than three, living in an urbanized area. All other variables are set to their mean values.

more-variable results. Increases in employment or employment-to-population ratios lead to increases in the one-year exit rate between 6.1% and 15.4%. For example, based on the model with county and statewide time effects, a 10% increase in employment implies a 7.3% reduction in the one-year exit rate. While not shown here, similar increases in service or retail employment show slightly lower increases in the exit rate. An increase in the employment-to-population ratio of 3.5 percentage points leads to a 6.1% increase in the probability of exiting within one year. These changes can add up to large effects. For example, an increase in employment growth of 10% combined with a 5% real increase in earnings would lead to a 13% increase in the one-year exit probability (for the model with county and statewide time effects).

The simulations for returns to welfare are presented in table 9. The results again show large and consistent effects for employment and earnings. A 5% increase in real earnings leads to a 4.0%–7.7% reduction in the probability of returning to welfare within one year. The results for employment uniformly show that increases in job opportunities lower the risk of returning to welfare. Increases in employment lead to decreases in the one-year recidivism probability of between 5.6% and 14.7%. In particular, using the estimates for the model with county and statewide time effects, a 10% increase in employment results in a 7.2% reduction in the one-year return rate, an increase in the employment-to-population ratio of 3.5 percentage points leads to a 7.4% reduction in the risk of returning to welfare.

These simulations generate a range of estimates for the effects of labor market conditions on exits from and reentry to welfare. We do not suggest a single estimate or model for two reasons. First, the confidence intervals on the estimates for the labor market variables are sizable, and, in many

TABLE 9.—PREDICTED EFFECT OF CHANGES IN LOCAL LABOR MARKETS ON REENTRY RATES
PERCENTAGE CHANGE IN THE PROBABILITY THAT A PREVIOUS RECIPIENT RETURNS TO AFDC WITHIN ONE YEAR

	Specification	URATE 7.5% to 4.5% (−3 p.p)	LN(E) 13.2 to 13.3 (Emp +10%)	E/POP 0.40 to 0.435 (+3.5 p.p)	EARN 6.7 to 7.0 (+5%)
Unemployment Rates Models					
County effects	Table 5(2)	−4.0%			−7.1%
County, time effects	Table 5(3)	−2.8%			−3.7%
County, time, county trend	Table 5(4)	−4.2%			−6.0%
Log Employment Models					
County effects	Table 6(2)		−6.0%		−6.6%
County, time effects	Table 6(3)		−7.2%		−4.0%
County, time, county trend	Table 6(4)		−14.7%		−5.4%
Employment/Population Models					
County effects	Table 7(2)			−5.6%	−7.7%
County, time effects	Table 7(3)			−7.4%	−4.5%
County, time, county trend	Table 7(4)			−7.1%	−6.5%

Notes: Each row represents the simulations based on a particular specification of the reentry model. The figures represent the percentage change in the predicted probability that the recipient returns to welfare within one year (relative to a baseline) resulting from a given change in each of the local labor market variables. The first two columns describe which model is being simulated. The baseline probability is 0.30, which is calculated for a white, single mother aged 25–34 with one child younger than three, living in an urbanized area. All other variables are set to their mean values.

TABLE 10.—PARAMETER ESTIMATES FOR EXITS AND REENTRY MODELS, BY DEMOGRAPHIC GROUP

		AFDC Family Type		Race/Ethnicity of Head		
	All	FG (Single Parent)	UP (Two Parent)	White	Black	Hispanic
			Panel A: Parameter Estimates for Exits from Welfare			
E/POP	2.509**	2.283**	3.571	0.860	0.984	5.409***
	(1.111)	(1.161)	(2.223)	(1.336)	(2.172)	(1.732)
	[6.1%]	[5.5%]	[8.1%]	[2.1%]	[2.4%]	[13.5%]
EARN	0.254***	0.272***	0.137	0.230***	0.342***	0.170
	(0.069)	(0.072)	(0.133)	(0.074)	(0.094)	(0.107)
	[5.9%]	[6.3%]	[3.0%]	[5.4%]	[8.1%]	[4.0%]
Log likelihood	−30011	−25708	−4170	−14766	−6572	−6849
Number of observations	181,728	155,442	26,133	79,997	45,181	40,900
			Panel B: Parameter Estimates for Reentry to Welfare			
E/POP	−2.671*	−2.207	−2.323	0.855	−3.713	−4.841**
	(1.458)	(1.520)	(2.782)	(1.737)	(3.409)	(2.220)
	[−7.4%]	[−6.2%]	[−6.3%]	[2.5%]	[−10.1%]	[−13.0%]
EARN	−0.168	−0.124	−0.297	−0.069	−0.141	−0.027
	(0.152)	(0.097)	(0.195)	(0.098)	(0.136)	(0.138)
	[−4.5%]	[−3.3%]	[−8.0%]	[−1.9%]	[−3.8%]	[−0.7%]
Log likelihood	−20451	−17765	−2776	−9717	−4858	−4992
Number of observations	236,566	204,107	32,459	116,795	48,845	53,448

Notes: Logistic models are estimated separately for each demographic group where the dependent variable equals 1 for a welfare exit (Panel A) or 1 for reentry (Panel B). Each specification also includes controls for family characteristics, GAIN variables, neighborhood variables, duration dummies, county-fixed effects, and time effects. Standard errors, given in parentheses, are adjusted for the grouped nature of the labor market variables. Asterisks indicate that the coefficient is significantly different from zero at the 10% (*), 5% (**), and 1% (***) level. The numbers in brackets [ ] are the percentage change in the one-year exit or reentry rate from the given change in the labor market variables and are constructed in the same way as tables 8 and 9.

cases, we cannot reject that they are equal across the specifications. Second, it is not clear what is the preferred specification for the fixed county and time effects. For example, including county time trends may get rid of some true variation. Having said this, it is somewhat reassuring that the ranges in the simulations in tables 8 and 9 are relatively tight.

The results in tables 8 and 9 suggest that labor market conditions play an important role in determining the transitions off and back onto welfare. But how large are these effects compared to other variables in the model? Likelihood-ratio tests show that labor market variables, demographic variables, duration dummies, and county and time effects each make statistically significant contributions to the model. The relative contribution of labor market variables, however, is quite a bit smaller than the other variables. The order of importance, using a ranking based on their incremental contribution to the pseudo R^2, is duration dummies, demographic variables, county dummies, time dummies, and labor market variables. Another comparison can be made between the simulated effects of the labor market variables (in tables 8 and 9) and the simulated effects of the demographic variables (in table 4). Demographic variables such as age, race, and family type have comparatively large effects on welfare participation.

D. Extensions and Sensitivity Analysis

Previous research has found significant differences in the responsiveness of different groups of welfare recipients to changes in tax and transfer environment. The earlier descriptive analysis showed that exit and reentry rates differ—in some cases substantially—across demographic groups. Accordingly, we may expect to see differences in their responsiveness to labor market conditions. Table 10 presents estimates from regressions estimated separately by demographic group. The specification for each is identical to the regression presented in column (3) of table 7 and includes the employment-to-population ratio and earnings, with county and statewide time effects. For comparison, the first column shows the comparable estimates based on the full sample. The top panel provides estimates for the exit model, and the bottom panel provides estimates for reentry. The standard errors are in parentheses, and the bracketed figures in the table give the percentage change in the probability that a (welfare or non-welfare) spell ends within one year resulting from a specified change in the labor market variable. In many cases, the differences between groups are not statistically significant, which is mainly due to the relatively large standard errors for the smaller subsamples. Nonetheless, exploring the patterns using the point estimates is suggestive.

Hispanics and blacks are more responsive to labor market conditions than are whites. This result is also found by Fitzgerald (1994, 1995), and it is consistent with the evidence that white women are more likely to leave welfare through marriage and less likely to leave welfare through employment relative to blacks (Bane & Ellwood, 1983; Blank, 1989; Blank & Ruggles, 1996). Further, AFDC-UP families are more sensitive to changes in employment opportunities than are single-parent families. This is not surprising, because AFDC-UP families contain two potential earners and they typically have more-substantial labor market experience and higher potential wages than single-parent recipients (Hoynes, 1996). This is also consistent with the aggregate caseload studies, which find greater sensitivity for AFDC-UP caseloads. (For example, see Blank (1997).)

In general, these results are consistent with the literature on the effects of local economic conditions on labor market outcomes of different demographic groups. Bartik (1991) and Bound and Holzer (1995) find larger responses to changes in economic conditions for blacks, less-educated workers, and older workers. They argue that this is due to lower migration rates among these groups. When the economy turns down, workers with lower propensities to migrate are hurt more by the downturn relative to those with higher migration propensities. This is an alternative explanation for the greater sensitivity among blacks, Hispanics, and possibly female-headed households.[37]

To control for possible effects of endogenous migration during the welfare spell, we have examined the impact of using the family's county of residence at the beginning of the spell (as opposed to contemporaneous location) to assign the labor market variables. Those results, not presented here, show that the estimates on the employment variable are reduced somewhat, but they remain statistically significant. The earnings parameter remains unchanged. The robustness to this extension is not surprising, because migration rates are fairly low in this population, especially between counties.[38]

It is possible that the composition of the welfare caseload may vary systematically with the business cycle. In bad times, the marginal new entrant is likely to have more education and experience than those joining the rolls during good times. If this is true, the main estimates will understate the true effect. In additional regressions, not provided here, several variables measuring the absolute and relative economic conditions during the period of entry were included, but they were never significant nor influential.

VII. Conclusion

This paper examines the impact in labor market conditions on AFDC participation and shows that welfare recipients respond in expected ways to incentives in the labor market. Transitions off welfare (exits) and transitions back onto welfare (reentry) are estimated using discrete duration models that control for local labor market conditions, demographic characteristics, neighborhood characteristics, duration effects, county-fixed effects, time effects, and county-specific time trends. The results show conclusively that, when earnings are higher and job opportunities are greater, recipients are more likely to leave welfare and less likely to return. This finding is quite robust. The findings do not rely on cross-area differences in economic conditions, but instead are identified by differences in the timing and severity of fluctuations across counties. Further, they are not driven by differences in unobserved county characteristics or the systematic selection of welfare-dependent individuals to bad neighborhoods.

An important contribution of the paper is its examination of the impact of several alternative measures of labor market opportunities including unemployment rates, log of employment, employment-to-population ratio, and average earnings. The results uniformly show that lower employment growth, lower employment-to-population ratios, and lower wage growth are associated with longer welfare spells and higher recidivism rates. Similar conclusions result from using overall employment or employment in services or retail trade. Overall, the results show that models that control for labor market conditions using employment-based measures perform better than unemployment rates.

The results show that a 10% increase in employment or a reduction in employment-to-population ratios of 3.5 percentage points—changes typical of the impact of the recent recession and recovery—lead to a 7%–15% reduction in the probability that a family leaves AFDC within a year and a 6%–15% decrease in the probability of returning to welfare within a year. A 5% increase in real earnings generates a 5%–7% reduction in the one-year exit rate. Hispanics, blacks, and two-parent families are more sensitive to changes in local labor market conditions. Overall, using the middle range of estimates, the combined effects of increases in employment and earnings lead to a 11%–12% increase in the likelihood that a welfare spell ends within one year and a 10%–11% decrease in the risk of returning to welfare within one year. These results are based on an analysis of California, a state with a generous AFDC program and a diverse population of recipients.

The lack of significant results in the previous literature has been attributed to two factors. First, local labor markets have typically been defined at the state level, which may be too large to reflect accurately employment opportunities. Second, small sample sizes have made it difficult or infeasible to include controls for labor market fixed effects, leading to possible biases. The results here suggest that the first factor may be the most important. In the regressions using unemployment rates (the measure used in most previous studies), the expected effect is found in the most simple model, without county or time effects.

To the question posed in the introduction—can economic growth significantly reduce reliance on public assistance?—

[37] The interpretation of these results is complicated by the presence of unobserved heterogeneity. For example, those taking up welfare as teens may be systematically different in terms of tastes for welfare and work, compared to women taking up welfare later in life. This confounds our ability to interpret the differences by age of head as "age effects."

[38] Long (1988), in a comprehensive analysis of migration patterns over the past three decades, finds the likelihood of moving within a county to be over 2.5 times more likely than moving across counties (within a state). This difference is particularly striking for public assistance recipients who are five times more likely to move within counties than across them. In the LDB sample, approximately 9% of families are observed to move across county lines. The probability of moving is higher for whites, younger heads, and families headed by women.

the results in this paper suggest that the answer is no. Optimistic assumptions about permanent increases in employment and earnings reduce but do not eliminate the demand for welfare. However, this is a case of whether the glass is half empty or half full. It is equally important to point out the significant relationship between economic conditions and welfare exits, which contributes to the mounting evidence that employment is an increasingly important route for achieving independence. With the implementation of time limits now commonplace in state welfare programs, it is important to rethink the possibility of linking these limits to local labor market conditions.

A somewhat broader policy question is to what degree do changes in economic conditions affect the AFDC caseload and program expenditures. The size of the caseload is determined by initial entry into welfare, length of spell, and recidivism, all of which may be affected by local economic conditions. The results here show that the length of welfare spells and the rate of recidivism are significantly affected by fluctuations in labor market opportunities. These results do not, however, speak to the importance of labor markets for initial entry into welfare. To the extent that the effects on entry are important, these results are an underestimate of the total impact of labor market conditions on welfare use.

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