WELFARE-TO-WORK TRANSITIONS IN FIVE URBAN AREAS:
Initial Results from the Pooled Multivariate Analysis

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Submitted to:

U.S. Department of Labor
Employment and Training Administration
Office of Policy and Research, Division of Research and Demonstration
200 Constitution Avenue, NW, N-5637
Washington, D.C.
202/219-7674, ext. 168 (Richard Muller)

March 2000

This report was prepared with funds provided through U.S. Department of Labor Agreement K-6558-8-00-80-60 to the Jacob France Center at the University of Baltimore. The views expressed here are those of the authors and do not represent the positions of the Department of Labor or the authors' institutions.

INTRODUCTION

In 1998, the U.S. Department of Labor's Employment and Training Administration, Division of Research and Demonstration awarded funding to an alliance of five state university partners to conduct research on welfare-to-work transitions in five large urban areas: Atlanta, GA; Baltimore, MD; Ft. Lauderdale, FL; Houston, TX; and Kansas City, MO. Each of the research partners had access to confidential administrative records for the universe of adult female welfare caseheads in each of these areas for the period 1992-1997. Both welfare and associated employment and earnings data were available. The objective of this phase of the analysis was to identify and explain similarities and differences in the welfare-to-work transition profiles of adult female welfare recipients in the five urban sites.

THE DATA

Each of the university-based research teams negotiated a data sharing agreement with the state agencies that maintain confidential welfare and employment and earnings histories for welfare recipients during the 1992-1997 period. These databases together include more than two million person-quarters of welfare, employment and earnings history.

This report concentrates on welfare-to-work transition profiles for all females ages 18-64 years who were a designated welfare casehead at any time between January 1992 and December 1997 in the following urban core counties: Baltimore, MD (a county-equivalent jurisdiction); Broward County, FL; Fulton County, GA; Harris County, TX; and Jackson County, MO. Table 1 lists the common variables that were available in the pooled dataset for these five areas.

Table 1. Variables Available for Analysis

AGE	Age of welfare recipient at beginning of quarter
TIME	Date of beginning of quarter, standardized as follows: 92= first quarter of 92, 92.25=second quarter of 1992, 92.5=third quarter of 1992, etc.
LONGTERM	Dummy variable equal to one if individual was on welfare for all of the four previous quarters, zero otherwise. (Missing for first year of data)
NUMKIDS	Number of children on welfare case.
BLACK	Dummy variable for case head being of Black race.
HISPANIC	Dummy variable for case head being of Hispanic ethnicity.
OTHER	Dummy variable for case head being minority but not BLACK or HISPANIC.
EXIT	Dummy variable equal to one if case head is absent from the welfare rolls the following quarter, zero otherwise.
UIWAGE	Amount of UI wages reported for case head for the current quarter.
EMPL	Dummy variable equal to one if case head has positive UI wages for the current quarter, zero otherwise.
EMPLEXIT	Dummy variable equal to one if case head disappears from welfare the following quarter, and has positive wages in the following quarter, zero otherwise.

Additional variables were created using these original data. For example, AGE and TIME were used to create AGESQ, the square of age, and TIMESQ, the square of TIME. UIWAGE was used to create the variable LNUIWAGE, its natural logarithm. Each of the research teams is investigating the possibility of acquiring additional data elements, including the reported education level of the case head, an especially important variable.[1] With additional data, we hope to expand the set of core data elements available and thus enhance our model specifications and the resulting analysis.

The data were organized by *case-quarter*. Each observation represents the welfare and/or employment status of an individual casehead for a reference quarter. Receipt of cash assistance for one or more quarters in a reference quarter defines the casehead as a recipient for the designated quarter. This convention is necessary because, while welfare data are available on a monthly basis, employment and earnings data drawn from UI wage records are only available quarterly.[2] This approach to organizing the data is based on the seminal work of Boskin and Nold (1975), that has become one of the standard approaches of event history analysis. Appendix A provides summary statistics for these data, showing the number of observations and means for the core variables described above.

MODEL SPECIFICATIONS

Functional Form

The data were used to fit reduced-form regression models in which outcomes were dependent on exogenous (or predetermined) variables. The outcomes of interest here are represented by the variables EXIT, EMPL, EMPLEXIT, UIWAGE, and LNUIWAGE. The exogenous variables include: AGE and its square, TIME and its square, LONGTERM, NUMKIDS, BLACK, HISPANIC, and OTHER. The race/ethnic variables are mutually exclusive and exhaustive, and consist of four categories: Black, Hispanic, White, and Other. In the regressions, White is the excluded category in the regressions.

The effects of AGE and TIME enter the model through a quadratic transfer function of the form $y=m+ax+bx^2$, in which y is the outcome, and x is either AGE or TIME. This allows the relationship between y and x to take a curved shape rather than forcing it to a straight line. This flexibility is indicated for AGE because a person's welfare use is expected to decrease in later years as dependent children reach school age and the casehead can more easily pursue work and/or other activities. The quadratic form was used for TIME because preliminary regressions using dummy variables for time revealed a curvilinear relationship. The key point for both AGE and TIME is that the estimated effect of each variable on a defined outcome tends to differ as the value of AGE or TIME changes.

[1] For more on the importance of education for analyzing welfare dynamics, see: Elwood (1986) and King and Schexnayder (1988), among others.
[2] See Hotchkiss et al (1999) for more detail on definitions of quarterly welfare receipt, employment, exits and other measures, as well as for descriptive results.

The regressions were fitted by ordinary least squares (OLS). Ideally, categorical variable procedures such as LOGIT or PROBIT would have been applied for the dummy endogenous variables, and a truncated variable procedure such as TOBIT would have been applied for the limited dependent variable UIWAGE (and its logarithm). These more appropriate procedures may be used in our subsequent research, but their use was beyond the scope of this exploratory analysis.

Tests of Across-Site Restrictions

In addition to executing the regressions, a series of F-tests of linear restrictions on the regression coefficients across the sites was performed. These F-tests are designed to test for commonalties and differences between the sites. The null hypothesis of the test is that one or more coefficients are equal for all five sites. Under the null hypothesis, the imposition of valid equality restrictions on the estimated coefficients should have little effect on the sum of squared errors (SSE) of the regressions. Since the SSE will usually rise when the coefficients are restricted, the question is whether the rise is large enough that it is unlikely to be due to sampling error. Answering this question is the purpose of the F test.[3]

Ideally, such restrictions should be tested with likelihood ratio tests. rather than F-tests. The F-test is theoretically inappropriate here because it relies on the maintained hypothesis that the error term of the regressions is normal, but in the case of the categorical and truncated variables in this research, this assumption is violated. The use of "incorrect" procedures is defensible on the grounds that when the sample size is large, it provides an excellent approximation to the results one would get from the "correct" procedures. In previous large-sample applications where the more demanding procedures as well as the simpler OLS-based procedures have been performed, the results of the statistical inference were quite similar (e.g., Schexnayder et al. 1998).

Results

This section reports the F-test and regression results. Each subsection concentrates on results for one of the four key dependent variables: EXIT, EMPL, EMPLEXIT, and UIWAGE. The detailed statistical results on which these highlights are based appear in Appendix B.

Exits from Welfare (EXIT)

The mean of the variable EXIT is the estimated probability that a welfare casehead in a reference quarter will be off welfare in the following quarter. This mean ranges from a low of 9.6 percent in Fulton County (GA) to a high of 24.0 percent in Broward County (FL). A higher welfare exit rate can be interpreted two ways. In Harris County (TX), the relatively high exit rate of 16.0 percent may be a manifestation of a revolving-door situation in which low-income families cycle on and off welfare at the mercy of economic and seasonal conditions over which they have little control. To some extent, welfare in Texas may have been serving as a *de facto* unemployment insurance program for single mothers working in low-wage jobs. The high exit rate estimated for

[3] The details of the test are covered in most econometrics texts. See for example, Green (1997), section 7.2.

Broward County (FL) may be tentatively attributed to the results of Florida's implementation of the WAGES program with "hard" two-year time limits on welfare use and the subsequent reduction in the area's caseload over the time period covered by the data. The relatively low exit rate estimated for Fulton County (GA) suggests that in that state, once a person goes on welfare, she is likely to remain on for a long time.[4]

The coefficients of the exogenous variables may be interpreted as showing the change in the probability of exit in a quarter relative to the change in the exogenous variable. Using the Baltimore City (MD) regression as an example, the first table in Appendix B shows that the exit rate for a long-term welfare recipient will be 0.03 less than for a similarly situated individual who is not a long-term recipient. Since the mean exit rate for Baltimore caseheads is only 0.09, the decline of 0.03 associated with being a long term recipient is substantial.

Also, each additional child will reduce the probability of exit in Baltimore by 0.01. Being Black will reduce the probability of exit in Baltimore by 0.03 relative to a similarly situated White casehead. Being Hispanic increases the probability of exit by 0.03 relative to a similarly situated White, while being of Other minority status decreases the exit rate by 0.01 relative to a similarly situated White person.

Age enters the exit equation through the quadratic function. For young welfare recipients, growing older has the effect of increasing the probability of exit, but when the recipient is older, growing still older has the effect of reducing the probability of exit. This suggests that older welfare face more serious barriers to exit than similarly situated young mothers.

Two approaches were used to estimate the effect of TIME on welfare exits. In one set of regressions, time was specified as a set of dummy variables representing all the quarters in the dataset. These regressions are not reported here but are available on request.[5] The purpose of the dummy variable specification of time was to allow the data to be free to show any discontinuous jumps in the exit rate. If state welfare waivers and/or the federal Personal Responsibility Act have been driving welfare exits over the period, then the dummy variable approach to modeling the effects of time would have produced a set of coefficients with a marked discontinuity at the point of introduction of the initiatives.[6] However, we observed no such discontinuities in the data for any of the sties. Instead, a slight seasonal effect was noted, and an overall curvilinear response to time was observed. By the principle of Occam's razor, the simpler specification with TIME and TIMESQ was chosen over the more complex, dummy variable technique. Further analysis will be conducted in the future.

[4] The expected value of time on welfare is the reciprocal of the exit probability. Thus, in Broward County (FL), the expected time on would be 4 quarters, but in Fulton County (GA), it would be 14 quarters.
[5] Contact J.A.Olson@mail.utexas.edu.
[6] For more on this debate see Bishop (1998), Moffitt (1999) and others.

Figure 1. The Effect of Age on Exits

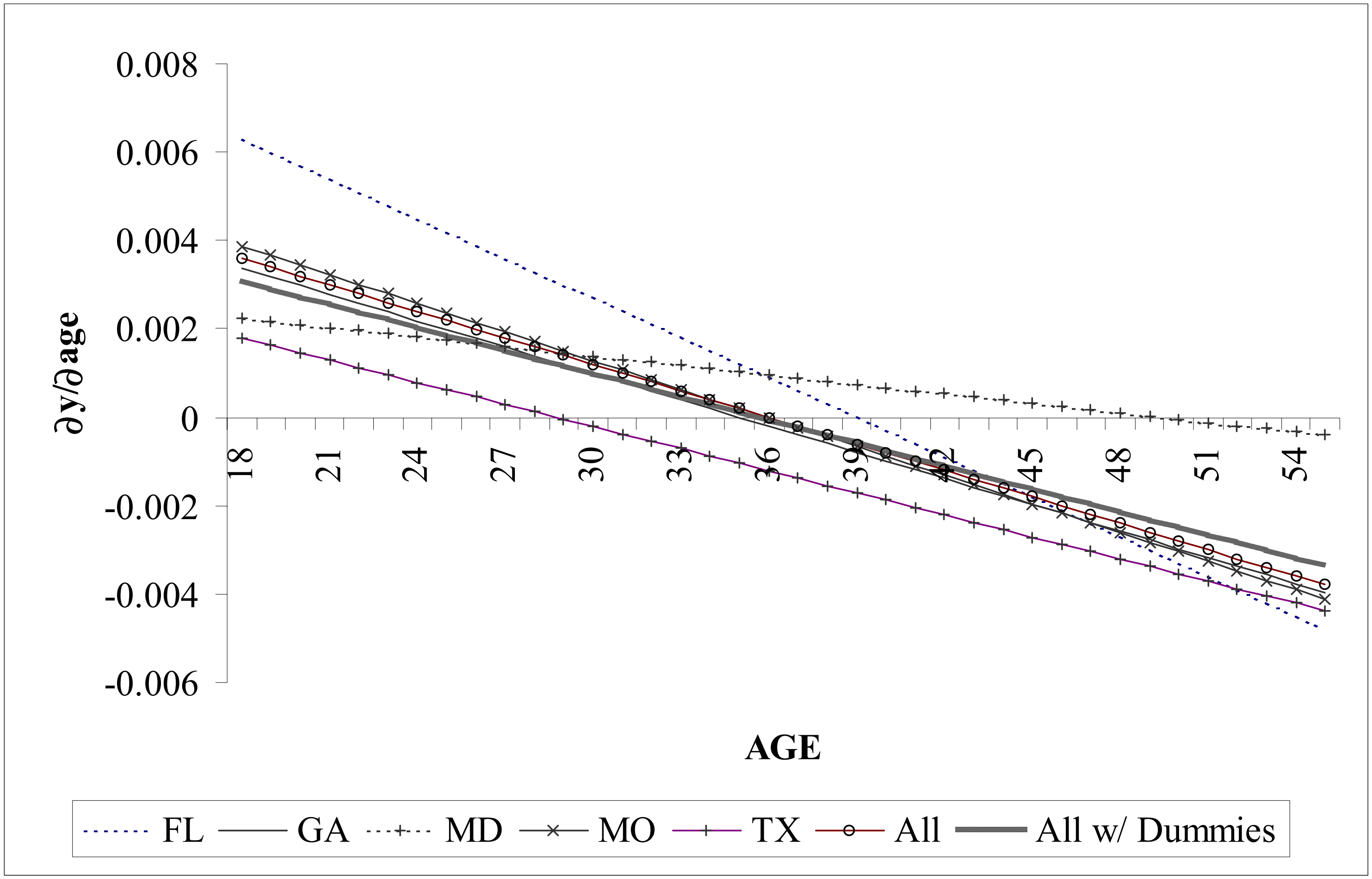
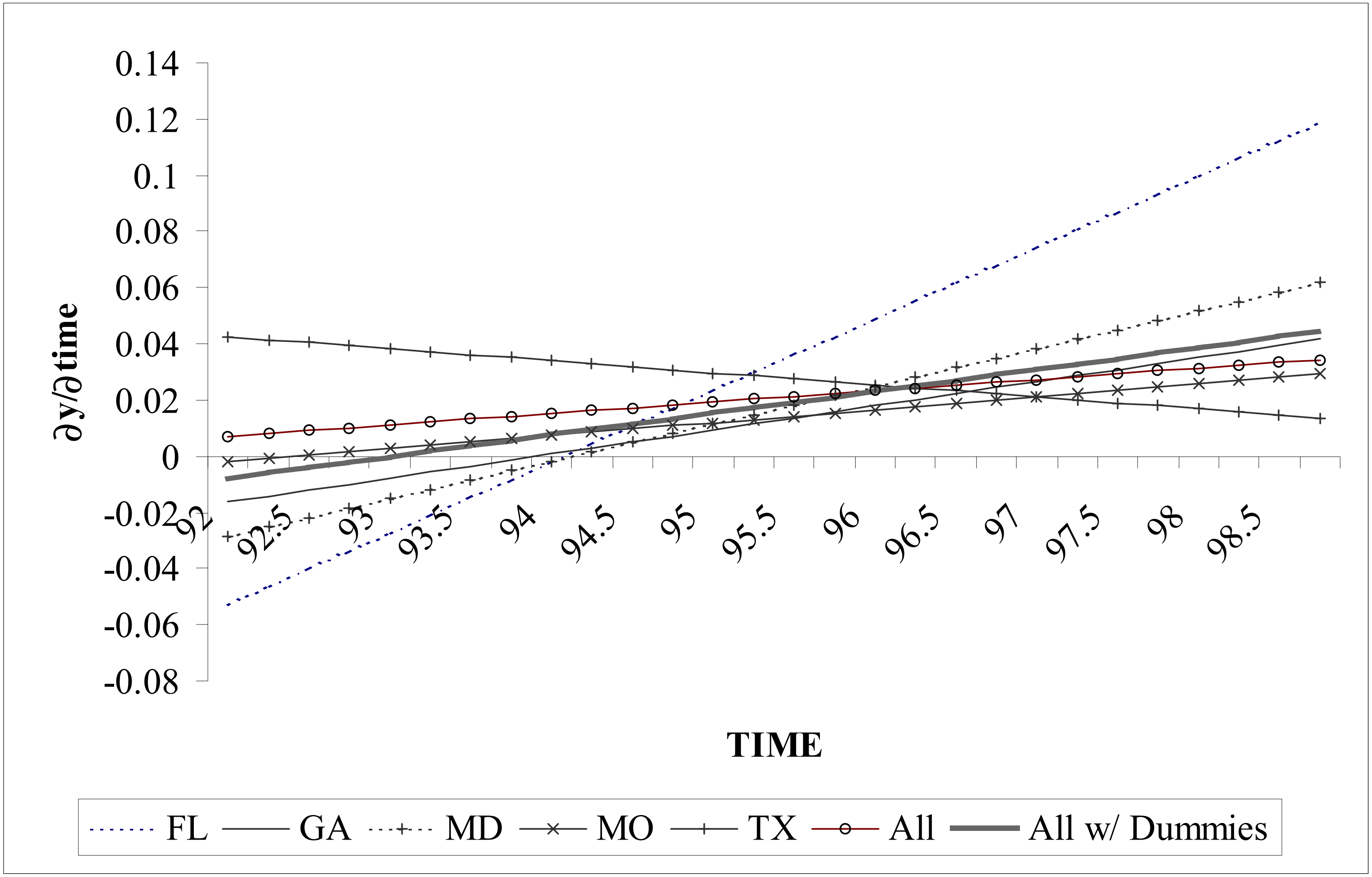


Figure 2. The Effect of Time on Exits



In Baltimore (MD), the coefficient of TIME in the EXITS equation was –1.2592, and the coefficient of TIMESQ was 0.006688. In the beginning of the sample when TIME=92, ∂y/∂TIME=-0.02857. Five years later, when TIME=97, ∂y/∂TIME= 0.03831. See Figure 2. This situation may be interpreted as suggesting that in 1992, as time passed, the probability of exiting would decrease, but in 1997 as time passed the probability would *increase*. We can solve for the date when the reversal took place—approximately February, 1994. This date coincides approximately with the onset of the nationwide downward trend in welfare caseloads.

This discussion has used Baltimore (MD) as the example. Can these observations be generalized to the other four sites? The answer is a qualified yes. If all of the sites were characterized by the same underlying caseload dynamics, then we would expect to see the coefficients of the regression differ between sites only by sampling error. All of the F-tests for whether the coefficients are the same across sites resulted in rejecting the null hypothesis that the coefficients were identical. However, this rejection is misleading because of the very large number of observations in the regressions. One of the most fundamental properties of most hypothesis tests is that, as the sample size increases, the power of the test also increases. In the limit, if sample size were to become infinite, even an infinitesimal difference between coefficients would be statistically significant. Since our sample size is very large, very small differences may show up as statistically significant, even though in an operational context the differences may be regarded as negligible or inconsequential.

Using the coefficient for BLACK as an example, we observe that the range of estimated coefficients in the EXIT equation runs from a low of –0.0389 to a high of –0.0265. The null hypothesis of commonality between the states is soundly rejected by the F-test, but the coefficients are very similar in the operational sense—they are all small negative numbers. Being BLACK reduces your chances of exiting welfare by about 0.035 ± 0.008, regardless of the site. The same cannot be said for being HISPANIC or OTHER. In the Florida, Missouri, and Texas sites, being HISPANIC reduces the chances of exiting welfare by about 0.01, but in the Georgia and Maryland sites, being HISPANIC actually *increases* the probability of exit by about 0.02. The coefficients for OTHER range from –0.0452 to 0.0202, indicating that being OTHER can affect one's probability of exiting welfare differently, depending on the site. These differences may also stem from the fact that Hispanics in Texas are overwhelmingly Mexican-American, while in other sites they may be Cuban, Puerto Rican or some combination of other ethnic groups. Thus, even though the F-test was rejected for HISPANIC, BLACK and OTHER, the operational significance of the rejections appear quite different.

The coefficients in the Broward County (FL) regression appear to be the most divergent of the five states, whether due to differences in the underlying parameters or differences in the way the data were prepared. Excluding Broward County, the results of the EXIT regression show more commonalities than differences between the states. The graphs of the effects of AGE and TIME show that the effects cluster together and have approximately the same magnitude and slope. The coefficients for LONGTERM are all negative, and excluding Broward County (FL), are in a relatively narrow range from –0.072 to –0.032. The coefficients for NUMKIDS are all negative and, again excluding Broward County (FL), fall in a relatively narrow range from –0.0113 to –0.0085.

The coefficients for OTHER in Broward and Fulton Counties and Baltimore and the coefficient for HISPANIC in Jackson County are the only coefficients that are not significantly different from zero. That most of the coefficients are statistically significant is another manifestation of the large sample sizes. Part of the reason the OTHER and HISPANIC coefficients show up insignificant is that there are so few observations for OTHER and HISPANIC in the affected areas. When the sample size for a subset of the observations is small, the standard error of the coefficient will be large. For example, the lack of significance of the OTHER coefficient in Fulton County (GA) may be due at least in part to the fact that only 0.3 percent of the sample is OTHER. Because of this small sample size, the standard error of the OTHER coefficient is quite large—four times larger than the standard error of the BLACK coefficient.

Analysis of Employment (EMPL)

It is not at all unusual for welfare caseheads to be employed and receiving welfare at the same time, a pattern that has been evident in related studies since at least the 1970s (e.g., Levitan et al. 1972, Goodwin 1972). In fact, over our entire sample almost thirty percent of the quarters spent on welfare were quarters of employment as well. The employment rate ranged from a low of 24 percent in Baltimore (MD) to a high of 41 percent in Jackson County (MO). Policy differences are likely to account for at least some of this difference. In some sites, particularly those in lower-benefit states, it takes very little in earnings to make a person ineligible for welfare—almost any low-wage job will cause a person to be removed from the caseload once the brief period of earnings disregards has been exhausted. In addition, concurrent welfare and work appears artificially higher in our analysis due to the use of quarterly periods. A casehead could be on welfare for months one and two of a quarter and exit to employment in month three but using quarterly data would appear to be contemporaneously receiving welfare and employed. This is a downside to relying mainly on quarterly UI wage records as the data source for employment and earnings.

The analysis of employment is very similar to the analysis of welfare exits overall, in that most of the regression coefficients are statistically significant, and all of the F-tests for equality of coefficients between sites are rejected. The coefficients for LONGTERM and NUMKIDS are similar across all five sites. The effect of TIME and TIMESQ is similar for all sites except Broward County (FL). However, coefficients for all other variables are quite different between sites. With regard to the effect of AGE and AGESQ, the plot of ∂EMPL/∂AGE is downward sloping for all sites but Baltimore. But, even among the sites with downward slopes for the employment/age relationship, there is little similarity. The slopes and magnitudes for Fulton County (GA) and Broward County (FL) are quite different from those of Harris County (TX) and Jackson Coutny (MO).

Figure 3 The Effect of Age on Employment

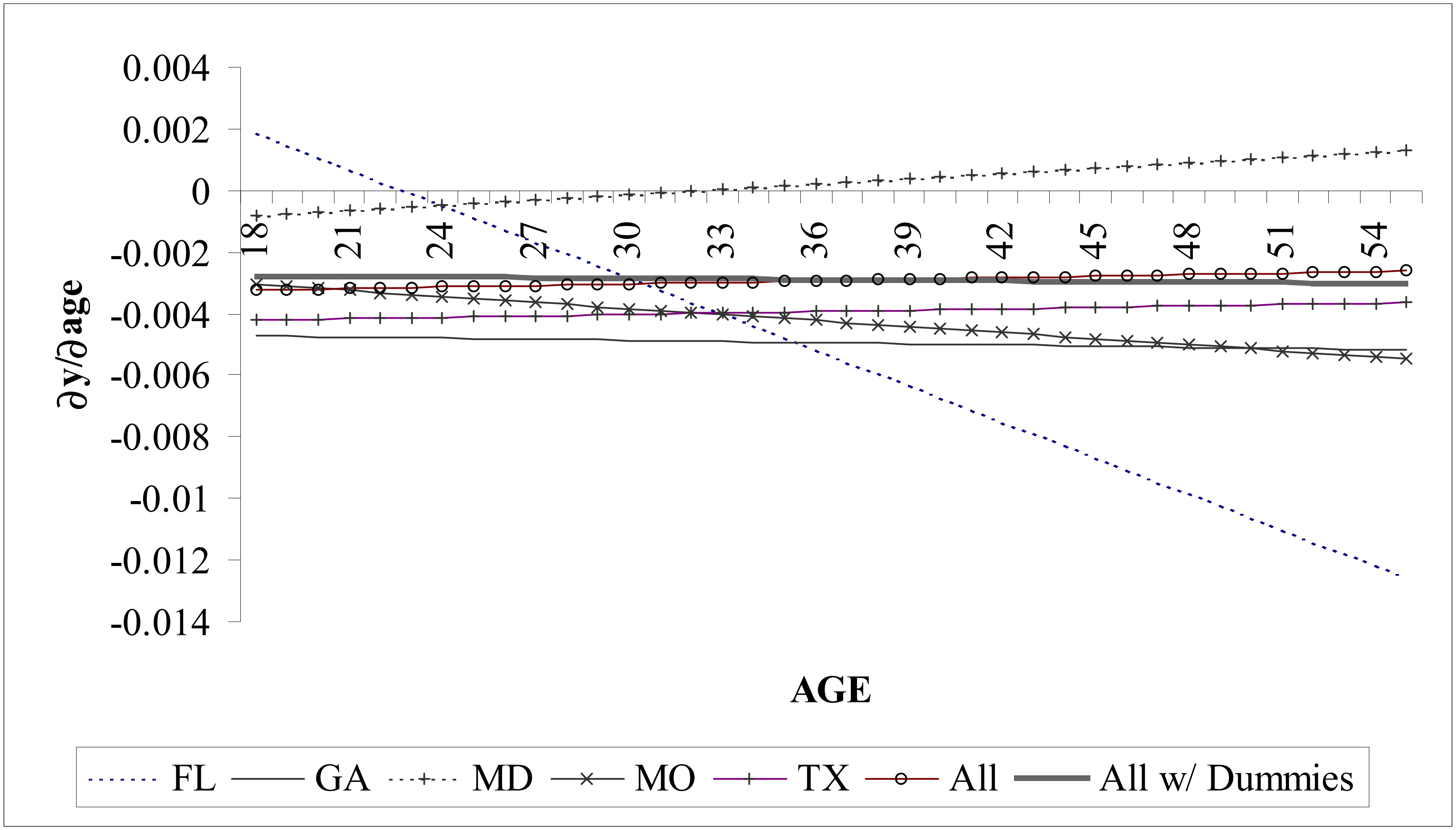
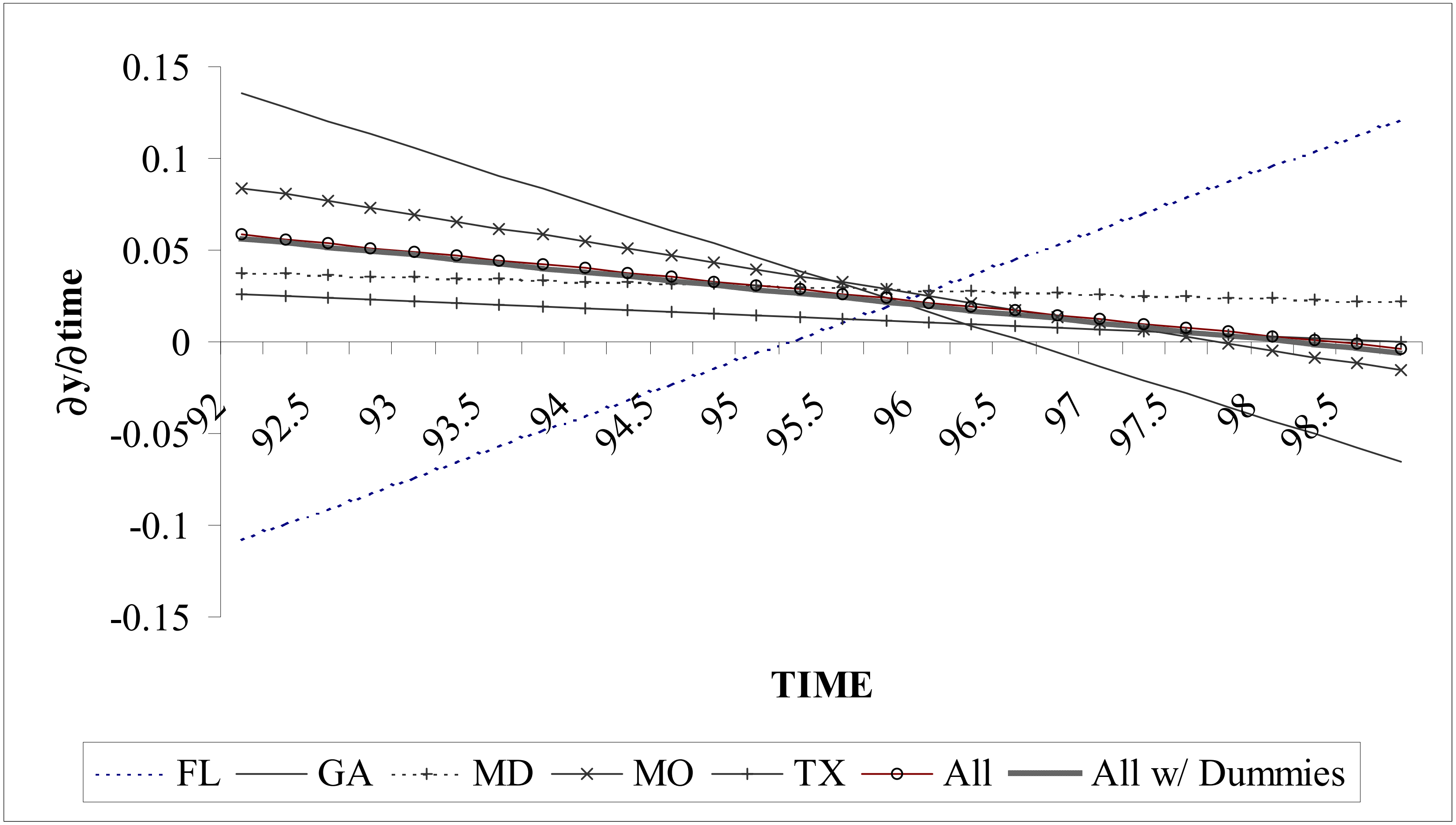


Figure 4 The Effect of Time on Employment



The effects of the race/ethnic variables also vary across sites. While the BLACK coefficients for all sites are positive, indicating that Blacks on welfare are more likely to be employed than Whites, the magnitude of the effect is twice as large in Jackson County (MO) as in Baltimore. The width of the range from lowest to highest is almost 0.08, a large number when you consider that the overall probability of employment predicted is only about 0.30. The situation is similar for HISPANIC. The HISPANIC coefficient ranges from a low of –0.062 in Harris County (TX) to a high of 0.051 in Jackson County (MO).

The wide divergence of the race/ethnic variables suggests that the underlying milieu of racial discrimination, race/ethnic culture and their interaction with welfare dynamics vary considerably between sites/states. For example, being Hispanic in Texas places a person among a sizable (25 percent in 1990) and cohesive minority of overwhelmingly (91 percent) Mexican-American origin, while being Hispanic in Missouri places a person in a tiny minority (1.2 percent in 1990) of possibly mixed Hispanic origin.[7] Note that the figures for our samples are similar: more than 31 percent of welfare caseheads in Harris County are designated as Hispancic, compared to only 2 percent of those in Jackson County.

One curious finding is that the BLACK coefficients are often positive and statistically significant, suggesting that they are more likely to be employed following welfare receipt than Whites. This outcome is consistent with some of our earlier work (Schexnayder et al. 1994), but still perplexing. Minorities tend to suffer from the effects of discrimination, are more likely to be hired into lower-paying jobs, and are often paid less than Whites in similar jobs. The explanation may lie in the fact that the population being analyzed is not all people in the labor force, but adult females on welfare. It may be that Whites on welfare are more likely to be unemployed because if they get a job, they will be paid a decent wage and will no longer be eligible for welfare, whereas jobs available to minority welfare recipients pay so poorly that the worker remains eligible for welfare even when employed. This enigma merits further analysis and may not be fully understood without the use of in-depth ethnographic research or other data sources and methods.

Analysis of Exits to Employment (EMPLEXIT)

The EMPLEXIT variable is designed to measure the desired outcome of leaving welfare and securing a job afterwards. In the entire sample, an exit from welfare took place in about 13.0 percent of the case-quarter observations, and an exit to employment took place in about 6.7 percent of the case-quarter observations. Thus, about half of the overall exits were associated with employment in the post-exit quarter, ranging from a low of 0.42 in Broward County (FL) to a high of 0.62 in Jackson County (MO). Since mere caseload reduction is a less desirable goal unless it is accompanied by some hope that the leaver will become employed and moving towards self-sufficiency, EMPLEXIT represents a more desirable outcome than EXIT alone.

[7] Earlier work by Schexnayder et al. (1994) has explored some of these issues more fully.

Since EXIT is a necessary condition to EMPLEXIT, it is not surprising that regressions for the two variables should show some commonalities. In fact, for the variables AGE, AGESQ, TIME, TIMESQ, LONGTERM, and NUMKIDS, the coefficients of the EXIT and EMPLEXIT equations are always statistically significant and of the same sign. As with the EXIT equations, most of the non-racial variables seem to be fairly comparable between the states, with Broward County (FL) being a possible outlier for some variables. For the race/ethnicity variables, especially BLACK, the situation is less clear. Some of the signs for the racial variables are contrary between the two equations, and some of the coefficients that are significant in one equation are insignificant in the other. For example, in Harris County (TX), being BLACK reduces the probability of exit by a statistically significant 0.0382, but *increases* the probability of an exit to employment by a statistically significant 0.008, both relative to Whites. Such anomalies were also evident in earlier research on the issue (Schexnayder et al. 1994) and merit further exploration.

Analysis of Earnings

The analysis of earnings is complicated by three difficulties. First, clearly not everyone in our sample is reported as having UI-covered earnings. Second, UI wage records data give only the sum of earnings for each employer for a given quarter, but no indication of the number of days or hours worked or the hourly wage paid. Third, for those who reported UI earnings, there is wide variation in the amount paid and the distribution of these earnings is strongly skewed to the right.

These difficulties have been only partially surmounted in this analysis. That approximately 70 percent of the case-quarter observations are characterized by zero wages can be overcome by using the TOBIT or other procedure that explicitly accounts for the truncated nature of the distribution of earnings. As a rough and ready approximation to the TOBIT procedure, we use the twin-linear probability function approach described in Goldberger (1964, p. 252). Using this approach, two OLS regressions are executed. In the first regression, the dependent variable is a dummy variable that has the value of one if there are earnings, and zero otherwise—this is our EMPL equation. In the second regression, the dependent variable is earnings, but the sample is limited to only those who had nonzero wages. The first regression tells us who becomes employed, and the second tells us how much they make, given that they are employed. This is the reason that the UIWAGE and LNUIWAGE regressions in this report only include only those observations for which UIWAGE>0.

Figure 5. The Effect of Age on EMPLEXIT

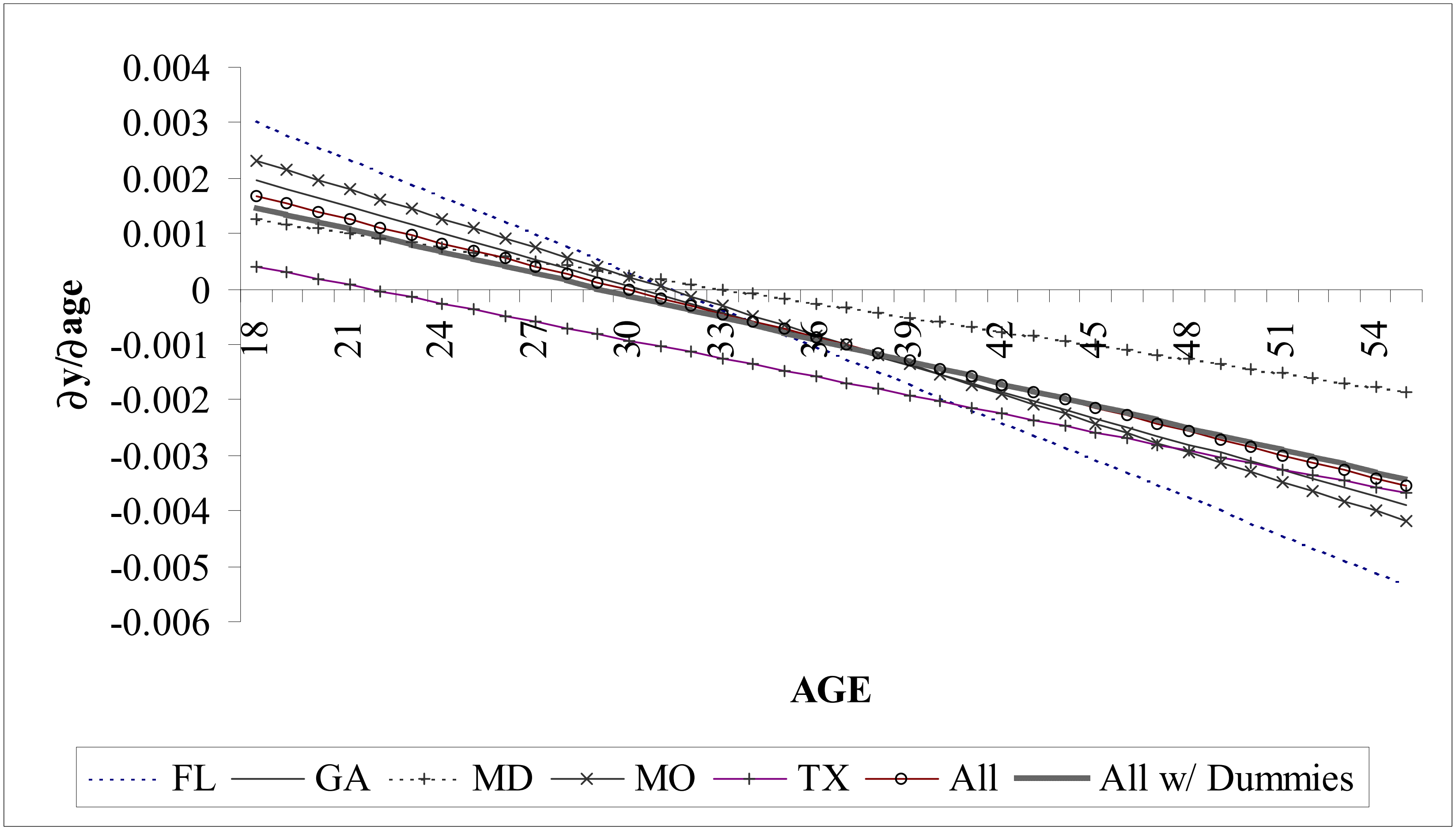
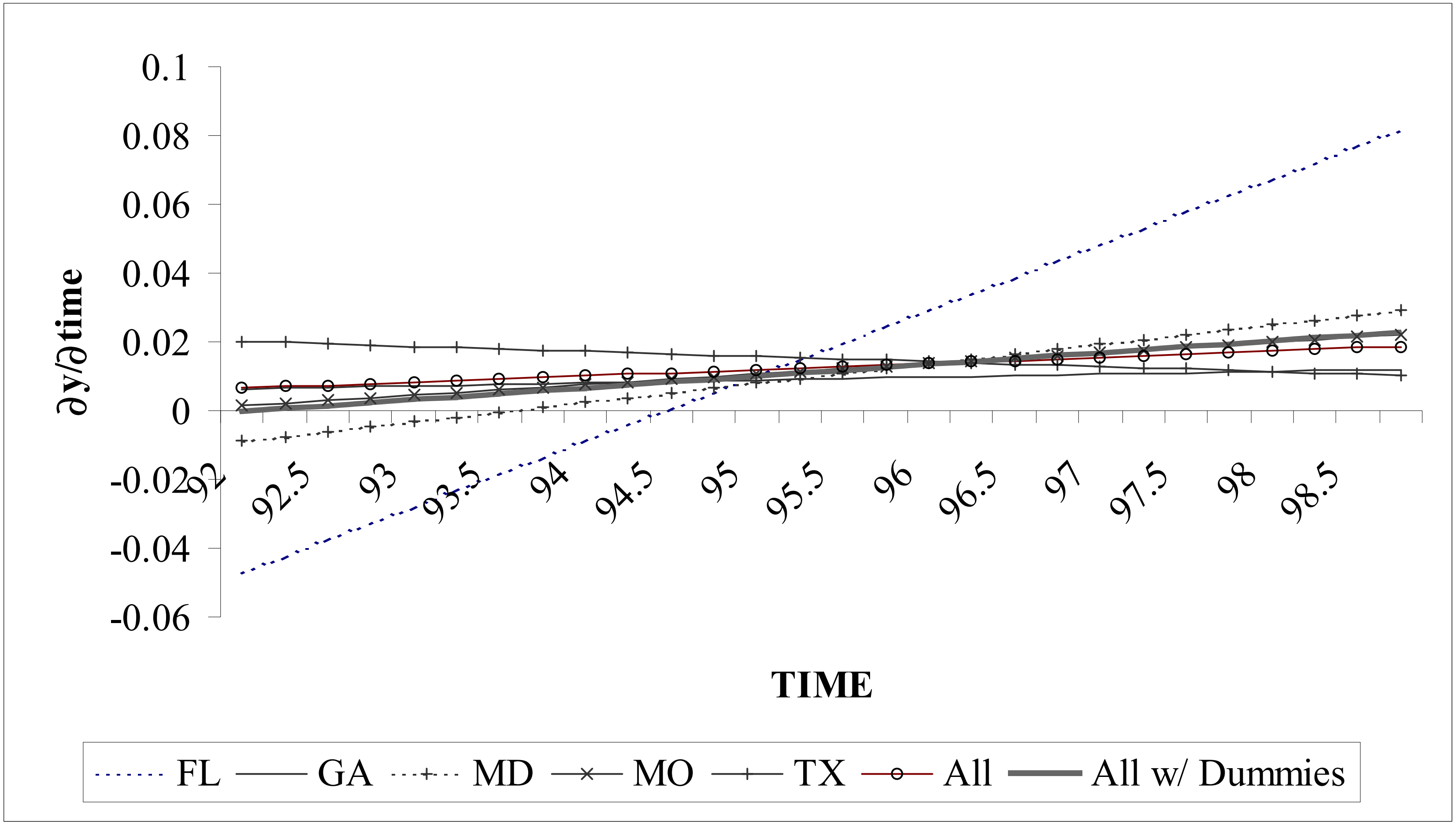


Figure 6. The Effect of Time on EMPLEXIT



The second difficulty, that we have only total wages for a quarter and no data on hours worked or hourly wage rates, is insurmountable. It is but one of the disadvantages of relying on UI wage records as the data source for earnings. Other disadvantages include the fact that geographic coverage is limited by state lines and that not all employment is covered.[8] In spite of these problems, UI wage records have become one of the standard sources for measuring earnings for welfare and other populations in such research. Our analysis comes with the usual *caveats* that accompany analyses relying on UI wage records data.

The third difficulty, that wages have a high variance and a skewed distribution, is partially ameliorated by modeling the logarithm of UIWAGE, rather than UIWAGE itself. The logarithmic transformation of wages reduces the skew of the dependent variable because extreme values of the variable translate to less extreme logarithms. The logarithmic transformation also affects the interpretation of the coefficients of the independent variables. In the linear equation, the coefficient shows the number of dollars the UIWAGE will change, given a unit change in the independent variable. In the logarithmic equation the coefficient shows the *percent* by which the dependent variable will change given a unit change in the dependent variable. Thus, in the Baltimore (MD) UIWAGE equation, the coefficient of 159.51 on the BLACK variable shows that a Black female who is on welfare and employed can be expected to earn $159.51 more per quarter than a similarly situated White female. In the LNUIWAGE equation for Baltimore (MD), on the other hand, the BLACK coefficient of 0.1165 shows that a Black female who is on welfare and employed can be expected to earn 11.65 percent more than a similarly situated White female. Since the mean of UIWAGES differs considerably among sites—e.g., the Baltimore (MD) mean is $1,149, compared to only $652 for Fulton County, GA—the logarithmic functional form makes comparisons across sites easier.

Because of the reduced sensitivity to outliers and the appealing interpretation of the coefficients, we believe the LNUIWAGE specification is superior to the simple linear specification. Thus, the following analysis concentrates on interpreting the coefficients found in the logarithmic equation. The linear UIWAGE specification is shown in the appendix. The results are very similar in most respects.

[8] Earlier papers by King (1989) and Stevens and Crosslin (1989) have described these limitations in detail. The inter-state data limitation is much more important for Baltimore and Kansas City than for the other sites since these sites have labor markets that straddle state borders. The Jackson County, MO site actually accessed UI wage records for both Kansas and Missouri.

Figure 7. The Effect of Age on LNUIWAGE

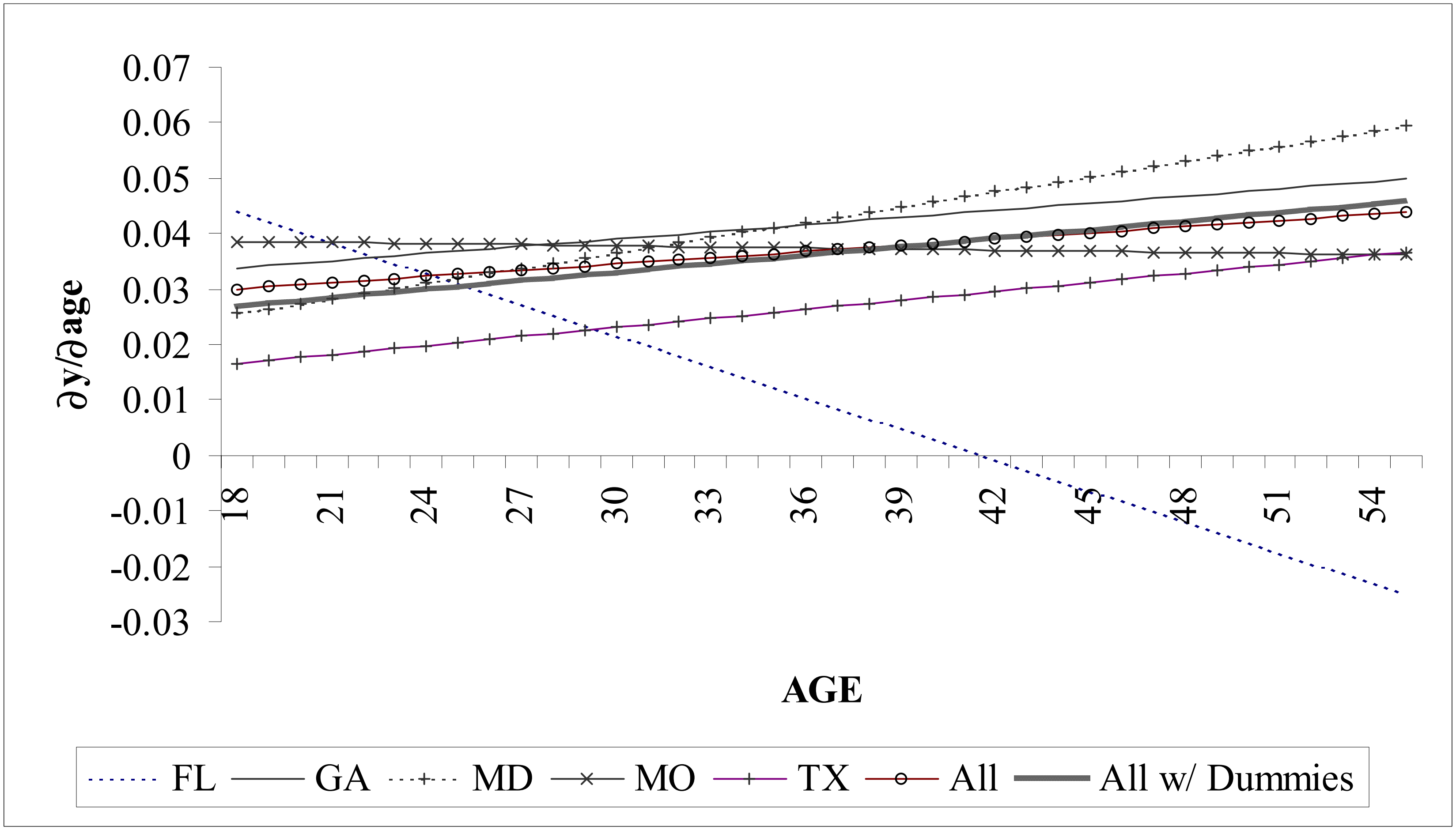
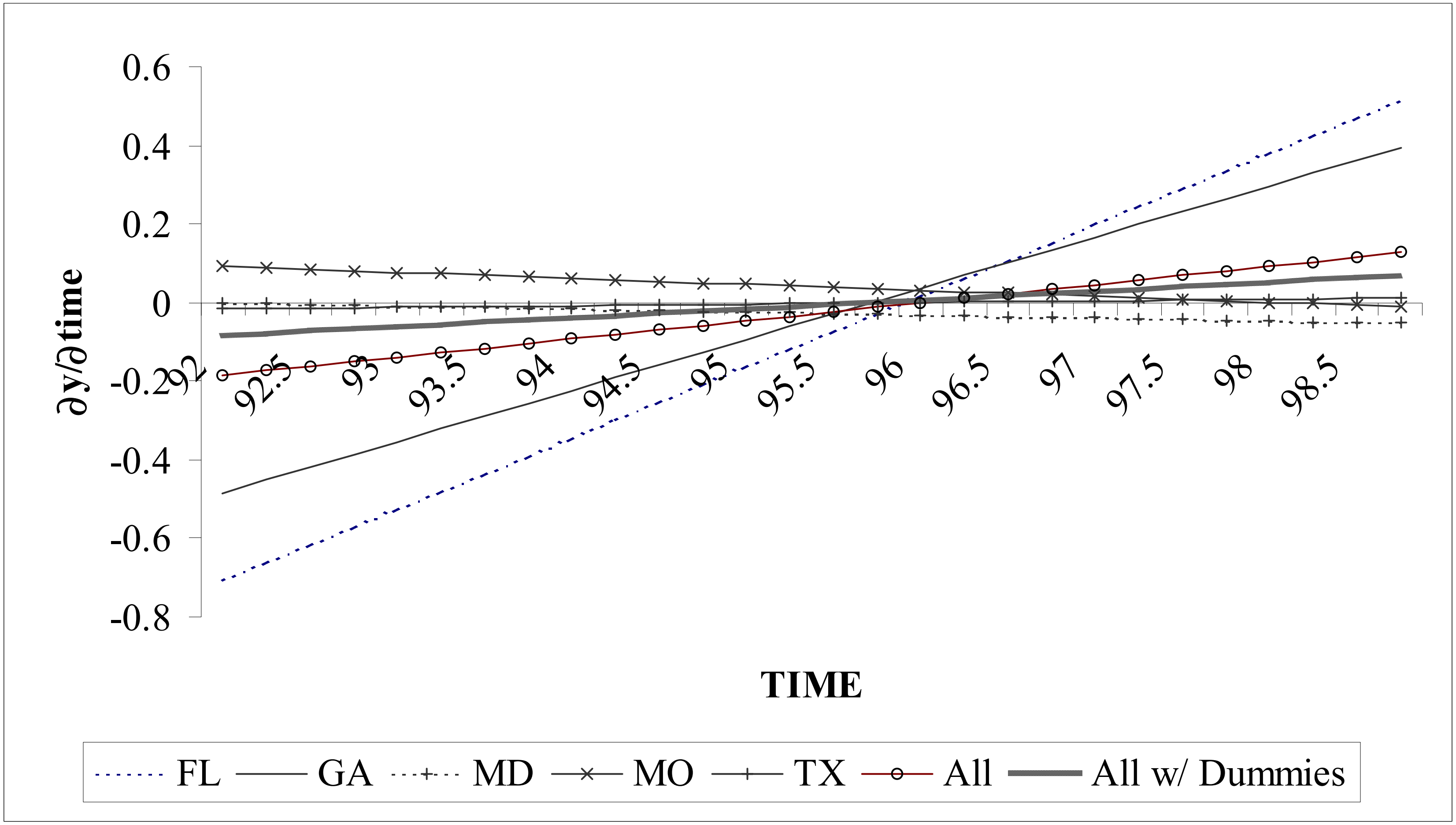


Figure 8. The Effect of Time on UIWAGES



The first thing to notice is the remarkable variation in the coefficients. In the earlier analyses, we noted that while the coefficients were significantly different, the differences between the coefficients tended to be quite small in an operational sense. This cannot be said of the coefficients for the LNUIWAGE equations. Glancing at the graph for the effect of TIME, we see the coefficients vary widely, some with positive slopes and some with negative slopes. The graph for AGE is somewhat better clustered, with only Broward County, FL appearing to be an obvious outlier. The effect of LONGTERM receipt is quite different among the sites, with coefficients ranging from –0.132 to –0.003. The BLACK coefficient ranges from –0.032 to 0.122.

Interestingly, the coefficients for all of the racial variables except BLACK and OTHER in Fulton County, GA are greater than zero. This phenomenon of higher pay for minority welfare caseheads is somewhat counterintuitive. Minority women may have more expertise than Whites in securing higher wage levels out of the low-wage labor market that is typically faced by welfare recipients. They may also have fewer non-market options and thus face greater pressures to earn more in the marketplace. This too is an area that merits further exploration.

SUMMARY AND CONCLUSIONS

This report has demonstrated the feasibility of pooling large welfare datasets for cross-urban analyses of welfare and work patterns. Comparison of the descriptive statistics and regression coefficients has shown both commonalities and differences among the states and the urban sites that are intuitively plausible. Most of the commonalities were found in the coefficients of the AGE, TIME, LONGTERM and NUMKIDS variables. The commonality of the TIME variable may be interpreted as indicating that the decline in caseload proceeded roughly uniformly among the states, despite varying implementation dates for different kinds of welfare reform measures among them (Hotchkiss et al. 1999). Note that, as in the other national analyses of welfare reform and caseload decline (e.g., Bishop, 1998, Moffitt 1999), these declines began well *before* reforms and may have more to do with labor market tightness and expansions in EITC, child care and Medicaid than welfare reform *per se*. Our more recent research (Mueser et al. 2000), however, makes a strong case for the effects of national and state reforms on these outcomes. The commonality of the variables AGE, LONGTERM and NUMKIDS may be interpreted as suggesting that despite other differences among the states, older people with a longer history of welfare dependence and more kids uniformly have a tougher time exiting welfare and/or becoming employed. The lack of uniformity among the racial variables indicates that race/ethnic patterns vary and that discrimination takes different forms in different areas of the country.

This preliminary analysis will be improved upon in the future through the use of more refined statistical techniques more appropriate to the limited and categorical variables being analyzed. We will also explore gathering data on additional variables such as educational attainment and achievement, child support receipt and earnings of non-custodial parents, childcare subsidies, and employer and industry variables (e.g., Bartik and Eberts 1999). Another approach may be to conduct more extensive analysis focusing on those areas that are able to provide a fuller set of demographic and related variables. Finally, we are expanding the sample other geographic locations, e.g., Cook County/Chicago.

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Appendix A—Summary Statistics

This appendix displays summary statistics for the data submitted by the five states. In order to show how the data change over time, the three tables are drawn from around the beginning, middle and end periods of the dataset, using only quarters for which all states had comparable data.

The following table shows summary statistics for observations of cases on welfare in the second quarter of 1994, the earliest date for which all variables are available. (The variable LONGTERM requires two years of prior data, so it is missing for the earlier years in some sites.)

	FL	GA	MD	MO	TX	ALL
Age	30.5	30.8	31.1	30.5	30.6	30.7
Black	61.2%	95.1%	87.1%	63.7%	50.7%	69.5%
Hispanic	11.3%	0.5%	0.2%	2.0%	31.2%	13.5%
Other Minority	0.8%	0.3%	0.5%	1.3%	2.2%	1.2%
Total Minority	73.3%	95.8%	87.9%	67.0%	84.1%	84.2%
White	26.7%	4.2%	12.1%	33.0%	15.9%	15.8%
Number of Kids	1.99	2.10	1.95	1.99	2.03	2.01
Exit Rate	19.6%	6.9%	7.0%	9.4%	17.7%	12.6%
Employment Rate	23.4%	32.3%	20.6%	38.8%	26.8%	26.9%
Rate of Exits to Employment	6.2%	4.1%	3.2%	5.7%	8.5%	5.9%
UI Wages (full sample)	226.78	196.43	235.80	398.03	262.99	255.19
UI Wages (employed only)	969.99	609.06	1,145.80	1,026.44	979.81	950.27
Long Term	54.7%	59.3%	76.6%	63.9%	57.9%	63.4%
Num of obs	13,401	21,748	37,159	13,683	54,384	140,375

The following table shows summary statistics for observations of cases on welfare in the first quarter of 1996, the approximate midpoint of the data.

	FL	GA	MD	MO	TX	ALL
Age	30.7	31.2	31.7	30.8	32.0	31.6
Black	62.3%	94.9%	87.8%	64.0%	50.3%	70.9%
Hispanic	12.5%	0.7%	0.3%	2.1%	31.2%	12.6%
Other Minority	1.0%	0.3%	0.5%	1.5%	2.3%	1.3%
Total Minority	75.7%	95.9%	88.5%	67.6%	83.8%	84.7%
White	24.3%	4.1%	11.5%	32.4%	16.2%	15.3%
Number of Kids	1.93	2.12	1.92	1.97	2.06	2.01
Exit Rate	20.5%	9.1%	8.3%	11.8%	18.5%	13.5%
Employment Rate	24.1%	36.6%	24.7%	40.1%	27.9%	29.5%
Rate of Exits to Employment	8.1%	5.7%	4.4%	7.3%	9.4%	7.0%
UI Wages (full sample)	207.53	210.76	306.30	435.73	280.00	285.86
UI Wages (employed only)	861.21	576.25	1,240.49	1,087.54	1,004.03	970.42
Long Term	51.3%	60.0%	77.2%	67.1%	63.4%	66.0%
Num of obs	10,731	20,914	34,140	13,121	43,276	122,182

The following table shows summary statistics for observations of cases on welfare in the third quarter of 1998. (For most variables, the data is available to the fourth quarter of 1998, but since the first quarter of 1999 is not available for all sites, exits could not be computed for some sites in the last quarter of 1998. Thus the third quarter of 1998 is the last quarter for which all data are available.)

	FL	GA	MD	MO	TX	ALL
Age	32.0	33.2	30.7	31.5	35.1	32.7
Black	68.7%	96.5%	89.4%	67.7%	56.0%	77.0%
Hispanic	11.4%	0.5%	0.2%	2.3%	26.0%	8.4%
Other Minority	0.8%	0.1%	0.4%	1.3%	2.2%	1.0%
Total Minority	80.9%	97.2%	90.1%	71.2%	84.2%	86.5%
White	19.1%	2.8%	9.9%	28.8%	15.8%	13.5%
Number of Kids	2.02	2.19	1.98	2.03	2.21	2.10
Exit Rate	16.4%	16.2%	17.6%	18.4%	21.0%	18.4%
Employment Rate	42.6%	29.7%	34.0%	47.9%	30.0%	34.6%
Rate of Exits to Employment	9.9%	8.1%	9.6%	12.6%	11.3%	10.3%
UI Wages (full sample)	564.21	307.11	273.98	544.46	311.83	346.32
UI Wages (employed only)	1,324.18	1,032.69	805.43	1,135.51	1,039.25	1,002.09
Long Term	34.7%	61.0%	63.1%	61.6%	62.8%	61.1%
Num of obs	2,523	11,934	18,500	9,287	16,914	59,158

Appendix B

This appendix displays regression results for the data submitted by the five states. In the tabulations of the regression coefficients, asterisks are used to designate the significance level of a two-tailed test of the null hypothesis that the regression coefficient is zero. Three asterisks indicate a the coefficient is significantly different from zero at the $\alpha=0.01$ level. Two asterisks indicate significance at the $\alpha=0.05$ level. One asterisk indicates the result is significant at the $\alpha=0.1$ level. Absence of asterisks indicates that the result is not statistically significant. The same notational scheme is used in the indication of the significance levels for the F tests. For the F tests, the null hypothesis is that a particular combination of regression coefficients are all equal.

Dependent Variable=EXIT

Indep Variable Coefficients	FL	GA	MD	MO	TX	All	All (With intercept Dummies)
INTERCEP	112.495066***	37.915893***	59.333808***	19.67138***	-21.946417***	16.460042***	33.670011***
FL							0.070173***
GA							-0.057704***
MD							-0.045561***
MO							-0.037488***
AGE	0.011713***	0.006942***	0.003535***	0.00776***	0.004795***	0.00719***	0.00623***
AGESQ	-0.00015***	-0.00009915***	-0.000035778***	-0.000108***	-0.000083395***	-0.000099886***	-0.000087017***
TIME	-2.390216***	-0.806686***	-1.259162***	-0.424865***	0.436113***	-0.363792***	-0.721985***
TIMESQ	0.012704***	0.004295***	0.006688***	0.002299***	-0.002139***	0.002016***	0.003882***
LONGTERM	-0.085203***	-0.050816***	-0.031639***	-0.055888***	-0.072069***	-0.064228***	-0.058074***
NUMKIDS	-0.016243***	-0.010209***	-0.011362***	-0.008521***	-0.01119***	-0.010554***	-0.010782***
BLACK	-0.034161***	-0.026904***	-0.026479***	-0.038854***	-0.038261***	-0.048147***	-0.034971***
HISPANIC	-0.010398***	0.022034***	0.028128***	-0.00606	-0.014194***	0.009102***	-0.008686***
OTHER	0.02022*	0.012267	-0.011043**	-0.015009***	-0.045155***	-0.02641***	-0.032494***
Summary Statistics							
Rsquared	0.040	0.019	0.021	0.019	0.024	0.027	0.036
Number of Obs	161,344	356,370	741,702	283,526	779,551	2,322,493	2,322,493
Mean of Dep Var	0.23998	0.09579	0.09566	0.11989	0.1599	0.13023	0.13023
s^2	0.175	0.085	0.085	0.103	0.131	0.110	0.109
SSE	28,240.18	30,293.82	62,842.52	29,339.65	102,208.05	256,044.99	253,707.74
SSR	1,187.63	572.36	1,320.52	577.80	2,511.81	7,018.76	9,356.01
SST	29,427.81	30,866.18	64,163.04	29,917.45	104,719.86	263,063.75	263,063.75

Tests of Linear Restrictions on Coefficients

Test	Number of Restrictions	F-test on Ho: Restriction is Acceptable
All Parameters Equal for All Regressions	40	895.502***
All Parameters Equal Except Intercept	36	199.850***
Intercept Equal for All Regressions	4	327.131***
AGE and AGESQ Equal for All Regressions	8	231.141***
TIME and TIMESQ Equal for All Regressions	8	411.9998***
LONGTERM Equal for All Regressions	4	360.6523***
NUMKIDS Equal for All Regressions	4	18.1604***
BLACK Equal for All Regressions	4	18.3823***
HISPANIC Equal for All Regressions	4	12.9767***
OTHER Equal for All Regressions	4	25.2397***

Dependent Variable= EMPL

Indep Variable Coefficients	FL	GA	MD	MO	TX	All	All (With intercept Dummies)
INTERCEP	153.891373***	-137.995131***	-13.343338***	-69.952614***	-18.43471***	-43.898902***	-43.936006***
FL							-0.055636***
GA							0.000659
MD							-0.067499***
MO							0.115779***
AGE	0.00888***	-0.004502***	-0.001849***	-0.00188***	-0.004488***	-0.003528***	-0.002613***
AGESQ	-0.000195***	-0.000006088	0.000028926***	-0.000032571***	0.000007711*	0.000008271***	-0.00000344
TIME	-3.230389***	2.869562***	0.25642***	1.443842***	0.383372***	0.902647***	0.90435***
TIMESQ	0.01697***	-0.01486***	-0.001188***	-0.00739***	-0.001941***	-0.004589***	-0.004606***
LONGTERM	-0.081185***	-0.102352***	-0.075742***	-0.088084***	-0.106132***	-0.1016***	-0.096113***
NUMKIDS	-0.009011***	-0.012422***	-0.019881***	-0.024165***	-0.007473***	-0.011654***	-0.013633***
BLACK	0.093807***	0.085405***	0.079236***	0.154032***	0.093303***	0.079264***	0.103281***
HISPANIC	0.000318	-0.015057	0.018749*	0.051962***	-0.062531***	-0.052595***	-0.042582***
OTHER	-0.020808*	-0.067858***	0.023184***	0.00521	-0.145659***	-0.093878***	-0.091424***
Summary Statistics							
Rsquared	0.042	0.032	0.025	0.047	0.046	0.033	0.047
Number of Obs	165,295	367,863	757,843	292,122	794,862	2,377,985	2,377,985
Mean of Dep Var	0.27291	0.35348	0.24989	0.4229	0.28431	0.30028	0.30028
s^2	0.190	0.221	0.183	0.233	0.194	0.203	0.200
SSE	31,413.28	81,407.10	138,434.64	67,926.63	154,300.59	483,287.75	475,942.33
SSR	1,386.39	2,661.26	3,621.04	3,367.47	7,436.54	16,351.12	23,696.54
SST	32,799.66	84,068.36	142,055.68	71,294.10	161,737.13	499,638.87	499,638.87

Tests of Linear Restrictions on Coefficients

Test	Number of Restrictions	F-test on Ho: Restriction is Acceptable
All Parameters Equal for All Regressions	40	1538.921***
All Parameters Equal Except Intercept	36	343.197***
Intercept Equal for All Regressions	4	468.2561***
AGE and AGESQ Equal for All Regressions	8	624.0713***
TIME and TIMESQ Equal for All Regressions	8	476.2313***
LONGTERM Equal for All Regressions	4	106.2428***
NUMKIDS Equal for All Regressions	4	153.1936***
BLACK Equal for All Regressions	4	270.7983***
HISPANIC Equal for All Regressions	4	142.6844***
OTHER Equal for All Regressions	4	172.845***

Dependent Variable=EMPLEXIT

	FL	GA	MD	MO	TX	All	All (With intercept Dummies)
Indep Variable Coefficients							
INTERCEP	85.050541***	2.957429	24.70717***	12.911149***	-8.038353***	7.05611***	14.535349***
FL							0.00679***
GA							-0.035945***
MD							-0.035152***
MO							-0.012195***
AGE	0.007099***	0.004794***	0.00278***	0.005473***	0.002399***	0.004225***	0.003871***
AGESQ	-0.000113***	-0.000079102***	-0.000042164***	-0.000087679***	-0.000055343***	-0.000070762***	-0.000066187***
TIME	-1.800792***	-0.070942	-0.527749***	-0.281812***	0.155593***	-0.159485***	-0.315041***
TIMESQ	0.009531***	0.00042*	0.00282***	0.001539***	-0.000736***	0.000902***	0.001712***
LONGTERM	-0.043709***	-0.029168***	-0.018784***	-0.031627***	-0.044215***	-0.037024***	-0.034009***
NUMKIDS	-0.009526***	-0.006541***	-0.007197***	-0.006927***	-0.004576***	-0.005738***	-0.00612***
BLACK	0.017622***	0.00578***	0.001562**	-0.006552***	0.007755***	-0.005765***	0.003454***
HISPANIC	0.006199**	0.013884**	0.00615	0.000072102	-0.02025***	-0.00727***	-0.018776***
OTHER	-0.00642	0.011514	-0.010454***	-0.005588	-0.037872***	-0.023997***	-0.029125***
Summary Statistics							
Rsquared	0.027	0.011	0.012	0.013	0.017	0.014	0.018
Number of Obs	161,344	356,370	741,702	283,526	779,551	2,322,493	2,322,493
Mean of Dep Var	0.10036	0.05633	0.04758	0.07478	0.08099	0.06712	0.06712
s^2	0.088	0.053	0.045	0.068	0.073	0.062	0.061
SSE	14,179.92	18,729.70	33,207.98	19,358.49	57,026.98	143,347.88	142,789.41
SSR	387.10	212.66	402.03	258.03	993.94	2,078.49	2,636.96
SST	14,567.02	18,942.36	33,610.01	19,616.52	58,020.93	145,426.38	145,426.38

Tests of Linear Restrictions on Coefficients

Test	Number of Restrictions	F-test on Ho: Restriction is Acceptable
All Parameters Equal for All Regressions	40	430.263***
All Parameters Equal Except Intercept	36	129.631***
Intercept Equal for All Regressions	4	152.658***
AGE and AGESQ Equal for All Regressions	8	138.3597***
TIME and TIMESQ Equal for All Regressions	8	234.8532***
LONGTERM Equal for All Regressions	4	219.8633***
NUMKIDS Equal for All Regressions	4	24.5054***
BLACK Equal for All Regressions	4	53.8337***
HISPANIC Equal for All Regressions	4	46.9617***
OTHER Equal for All Regressions	4	25.8846***

Dependent Variable=UIWAGE

Indep Variable Coefficients	FL	GA	MD	MO	TX	All	All (With intercept Dummies)
INTERCEP	918540***	494121***	-85200***	-34491***	37750***	171547***	83138***
FL							-16.483274***
GA							-342.176786***
MD							92.19608***
MO							121.473774***
AGE	47.050717***	-6.039249***	-8.7078***	12.038569***	0.744076	-1.591835*	-4.473723***
AGESQ	-0.473439***	0.503041***	0.802864***	0.466839***	0.412525***	0.568806***	0.60251***
TIME	-19152***	-10326***	1815.711949***	693.373541***	-774.972912***	-3566.964345***	-1730.497926***
TIMESQ	99.812754***	53.98673***	-9.605336***	-3.435467***	4.05349***	18.603511***	9.070939***
LONGTERM	-88.678164***	-72.994499***	-79.864839***	23.757485***	-76.772271***	-25.538403***	-60.649701***
NUMKIDS	-18.325083***	-34.304963***	-57.3757***	-87.668695***	-60.176801***	-63.552516***	-54.565615***
BLACK	56.766253***	-59.674561***	159.51033***	66.188982***	5.984699	-11.459756***	58.791382***
HISPANIC	47.35902***	60.530868*	49.668858	12.760848	24.068777***	27.122726***	60.126384***
OTHER	64.345508	-206.828463***	136.915141***	47.519706	-11.683346	29.697999*	30.583031*
Summary Statistics							
Rsquared	0.060	0.146	0.159	0.132	0.060	0.106	0.125
Number of Obs	45,111	130,032	189,378	123,539	225,988	714,048	714,048
Mean of Dep Var	957.2553	652.0887	1149.78985	1105.18478	1005.5752	993.63263	993.63263
s^2	915,459.907	564,249.853	1,313,187.349	1,109,857.846	1,171,652.228	1,110,541.744	1,086,252.280
SSE	41,288,157,246.00	73,364,894,408.00	248,675,661,959.00	137,099,629,861.00	264,767,627,250.00	792,969,005,758.00	775,621,060,387.00
SSR	2,652,858,840.90	12,536,492,993.00	47,146,692,345.00	20,804,794,346.00	16,825,720,670.00	93,609,279,800.00	110,957,225,171.00
SST	43,941,016,086.90	85,901,387,401.00	295,822,354,304.00	157,904,424,207.00	281,593,347,920.00	886,578,285,558.00	886,578,285,558.00

Tests of Linear Restrictions on Coefficients

Test	Number of Restrictions	F-test on Ho: Restriction is Acceptable
All Parameters Equal for All Regressions	40	809.837***
All Parameters Equal Except Intercept	36	270.210***
Intercept Equal for All Regressions	4	531.9858***
AGE and AGESQ Equal for All Regressions	8	635.8079***
TIME and TIMESQ Equal for All Regressions	8	474.171***
LONGTERM Equal for All Regressions	4	56.4442***
NUMKIDS Equal for All Regressions	4	68.1241***
BLACK Equal for All Regressions	4	64.5632***
HISPANIC Equal for All Regressions	4	0.604
OTHER Equal for All Regressions	4	4.9838***

Dependent Variable=LNUIWAGE

	FL	GA	MD	MO	TX	All	All (With intercept Dummies)
Indep Variable Coefficients							
INTERCEP	837.641652***	601.16921***	-27.092069**	-68.051724***	24.403067*	218.693532***	108.605931***
FL							0.003768
GA							-0.557743***
MD							0.03439***
MO							0.128515***
AGE	0.077763***	0.026054***	0.009109***	0.039778***	0.006816***	0.023288***	0.017813***
AGESQ	-0.000934***	0.000216***	0.000458***	-0.000033029	0.000271***	0.000187***	0.000256***
TIME	-17.370228***	-12.460159***	0.711853***	1.497406***	-0.384592	-4.442433***	-2.155832***
TIMESQ	0.09056***	0.065084***	-0.003871***	-0.007637***	0.002003	0.023135***	0.011273***
LONGTERM	-0.121153***	-0.13224***	-0.039514***	-0.003312	-0.120297***	-0.039908***	-0.080253***
NUMKIDS	-0.012641**	-0.054652***	-0.03448***	-0.081486***	-0.064945***	-0.065939***	-0.055123***
BLACK	0.045378***	-0.024882	0.116543***	0.122662***	0.060101***	-0.03255***	0.086309***
HISPANIC	0.094099***	0.300623***	0.123358*	0.159051***	0.109189***	0.112881***	0.13121***
OTHER	0.111588	-0.097152	0.095591**	0.238298***	0.12525***	0.139791***	0.141517***
Summary Statistics							
Rsquared	0.037	0.083	0.093	0.067	0.035	0.061	0.089
Number of Obs	45,111	130,032	189,378	123,539	225,988	714,048	714,048
Mean of Dep Var	6.26521	5.71264	6.3633	6.38645	6.29401	6.22069	6.22069
s^2	1.606	1.891	1.731	1.632	1.647	1.773	1.722
SSE	72,423.59	245,894.42	327,820.19	201,579.25	372,231.99	1,265,942.28	1,229,224.31
SSR	2,789.42	22,399.34	33,604.15	14,535.46	13,506.77	82,956.10	119,674.07
SST	75,213.01	268,293.76	361,424.34	216,114.71	385,738.76	1,348,898.38	1,348,898.38

Tests of Linear Restrictions on Coefficients

Test	Number of Restrictions	F-test on Ho: Restriction is Acceptable
All Parameters Equal for All Regressions	40	841.193***
All Parameters Equal Except Intercept	36	150.786***
Intercept Equal for All Regressions	4	357.6341***
AGE and AGESQ Equal for All Regressions	8	272.5136***
TIME and TIMESQ Equal for All Regressions	8	322.0225***
LONGTERM Equal for All Regressions	4	61.0825***
NUMKIDS Equal for All Regressions	4	42.1544***
BLACK Equal for All Regressions	4	17.4542***
HISPANIC Equal for All Regressions	4	3.5904***
OTHER Equal for All Regressions	4	3.4342***