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Shiferaw Gurmu
Georgia State University

Keith R. Ihlanfeldt
Florida State University

William J. Smith
Georgia State University

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Author correspondence

Shiferaw Gurmu, Andrew Young School of Policy Studies, Georgia State University, P.O. Box 3992, Atlanta, GA 30302

Keith R. Ihlanfeldt, DeVoe L. Moore Center and Department of Economics, 150 Bellamy Building, Florida State University, Tallahassee, FL 32306

William J. Smith, Fiscal Research Center, Andrew Young School of Policy Studies, Georgia State University, P.O. Box 3392, Atlanta, GA 30302

University of Kentucky Center for Poverty Research, 302D Mathews Building, Lexington, KY, 40506-0047
Phone: 859-257-7641; Fax: 859-257-6959; E-mail: ukcpr@uky.edu

www.ukcpr.org

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Does Space Matter to the Employment of TANF Recipients? Evidence from a Dynamic Discrete Choice Model with Unobserved Effects*

Shiferaw Gurmu[a], Keith R. Ihlanfeldt[b], William J. Smith[c]**

[a] Department of Economics, Andrew Young School of Policy Studies, Georgia State University, P.O. Box 3992, Atlanta, GA 30302, USA
[b] DeVoe L. Moore Center and Department of Economics, 150 Bellamy Building, Florida State University, Tallahassee, FL 32306, USA
[c] Fiscal Research Center, Andrew Young School of Policy Studies, Georgia State University, P.O. Box 3992, Atlanta, GA 30302, USA

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** Corresponding author: William J. Smith, phone (404) 651-1908, fax (404) 651-0416, e-mail joeysmith@gsu.edu.

Abstract

We study the factors affecting the employment probability of Temporary Assistance for Needy Families (TANF) recipients using recent quarterly panel data from Atlanta, Georgia. A central focus of our study is to determine whether the TANF recipient's proximity to job opportunity and the availability of childcare affect her probability of full-time employment. Both static and dynamic models of employment choice are estimated that control for unobserved individual effects. We estimate models separately for a sub-sample of TANF recipients living in public housing, whose residential locations can be considered exogenously determined. We find substantial evidence that individual and family characteristics (such as, the education of the recipient and the number of children and adults in her family) are important determinants of the employment probability of welfare recipients. On the other hand, space-related variables are found to be relatively unimportant.

JEL Classification: I38, R23, J15, C23

Keywords: Welfare-to-work, space, dynamic panel data, public housing residents

1. Introduction

The Personal Responsibility and Work Opportunity Reconciliation Act of 1996 imposes stringent work requirements and time limits on welfare recipients – recipients must find work within two years of receiving benefits and lifetime benefits are limited to a total of five years.[1] This legislation has heightened interest in the factors that affect the employment probability of welfare recipients. These factors can be divided into two categories – family/individual-based and place-based. The former category includes the standard set of human capital variables (education, training, and experience) as well as the recipient's attitudes, reliability, and motivation. Place (i.e., the recipient's residential location) may affect employment probability in a variety of ways, but the two that have been given the most attention are job accessibility and neighborhood effects. Job access refers to the nearness of job openings to the home location which the recipient is qualified to hold. Neighborhood effects encompass a variety of mechanisms whereby a recipient's neighbors may alter her/his willingness or ability to work.

Extant evidence on the effects of individual and place variables on the employment of welfare recipients, and low-skill workers generally, can be questioned because few studies have adequately dealt with the fact that residential location is self-selected. Biased estimates will result if unobservable characteristics of the individual affect both the choice of residential location (and thereby job access and neighborhood effects) as well as the probability of employment.

In the case of welfare recipients it has been argued that self-selection of residential location is not a major source of bias because recipients' residential choices are highly restricted by their low incomes (Allard and Danziger, 2002). However, there is also evidence that suggests that two of the key individual attributes that result in a recipient having a job are reliability and motivation (Regenstein et al., 1998), which are generally unobservable variables.

[1] The research presented in this paper is based on data from the state of Georgia, which limits lifetime benefits to only four years.

Even if low income limits residential choice, there may be enough choice that these variables are correlated with observable characteristics of the recipient's residential location that affect employment probability. For example, recipients more motivated to work may perform better in job interviews and may be more likely to seek a place to live that offers nearby job opportunities. It is not clear therefore whether self-selection of residential location is more or less of an econometric issue for welfare recipients in comparison to low-skilled workers generally.

There are two approaches toward dealing with self-selection: 1) conduct a random assignment experiment or identify a natural experiment where location is random, and 2) rely upon panel estimation techniques that control for unobservable individual effects. In this paper both of these approaches are taken to study the factors affecting the employment probability of Temporary Assistance for Needy Families (TANF) recipients living within the Atlanta, Georgia metropolitan area. We have assembled a unique panel of the quarterly employment experience of individual TANF recipients that contains both individual and place level variables. Both static and dynamic models of employment choice are estimated that control for unobserved individual effects. In addition, we estimate our models separately for a sub-sample of TANF recipients living in public housing, whose residential locations can be considered exogenously determined.

Besides addressing self-selection, our paper improves on previous studies in a number of respects. First, we estimate the TANF recipient's access to jobs at the block-group level quarterly, which provides a level of geographic and chronological detail not previously used. Second, we combine characteristics of the individual, the case, and the place (neighborhood and job access) in a single estimation where the relative importance of these factors can be established. Finally, the dynamic models we estimate are based on the dynamic nonlinear random effects approach recently proposed by Wooldridge (2005). This approach provides practical solutions to the initial conditions problem in nonlinear panel data models, such as the dynamic unobserved effects probit model employed in our empirical application.

We find strong evidence of positive state dependence and unobserved heterogeneity in the full-time employment participation behavior of welfare recipients. There is also substantial evidence that individual and family characteristics are important determinants of the employment probability of welfare recipients. The age and education of the recipient and the number of children and adults in her family are all found to be important. Space (neighborhood effects and job access), on the other hand, is found to be relatively unimportant. This confirms the findings of other recent studies that have focused on the employment of welfare recipients.

The next section provides background followed by a description of the data and the variables in Section 3. Section 4 details the estimation strategy and section 5 presents our results broken down by race. Section 6 presents our findings for a sub-sample of public housing residents and Section 7 concludes.

2. Background

There are two hypotheses that relate the employment probability of low skill workers to their residential locations – the spatial mismatch hypothesis (SMH) and the neighborhood effects hypothesis (NEH). The SMH, introduced by Kain in 1968, states that job suburbanization has reduced the employment opportunities of central city low- skill residents, because they have been unable to shift their labor supply from the central city to the suburbs. While Kain (1968) attributed this lack of a supply response to racial discrimination with the suburban housing market, others have argued that other factors also play a role, including suburban land use controls, lack of knowledge of suburban job openings, and the failure of public transportation to meet the needs of reverse commuters (Ihlanfeldt and Sjoquist, 1998).

Under the rubric of "neighborhood effects" falls a variety of mechanisms that link the neighborhood milieu to individual behaviors and opportunities. Examples include peer group influences, role model effects, and informal sources of job market information. While many other examples could be identified (see Ellen and Turner (1997) for a complete listing), the basic idea is well known – poor neighborhoods result in individual behaviors that are detrimental to both the person and society (Wilson, 1987).

Turning first to the empirical evidence on the SMH, it can be said that this evidence is quite extensive and generally supports the conclusion that the relatively low earnings and employment of less-educated minorities are partially attributable to their poor accessibility to suburban jobs.[2] However, the SMH literature has focused on males rather than females and on youth instead of adults. The concentration on males can be explained by their worse labor market outcomes and the belief that these outcomes are related to their high rate of incarceration and to high crime rates within central cities. These factors also help to explain the popularity of studying youth, but youth also provide a convenient approach to dealing with self-selection. The argument is commonly made that for youth still living at home residential location can be treated as exogenously determined by their parents or guardians.[3]

Because welfare recipients tend to have unique employment problems (for example, limited recent job experience and childcare needs), the results of spatial mismatch studies that have not focused specifically on them may not be applicable to them. In recognition of this, two recent studies investigate whether the SMH applies to TANF recipients.[4] Allard and Danziger (2002) use administrative data on welfare receipt and job location data from the Multi-City Study of Urban Inequality to examine the relationship between access to jobs and the employment probability of TANF recipients living in Detroit. Their logit employment models are estimated for two separate cross-sectional snapshots – June, 1996 and June, 1998, and

[2] For reviews of the SMH literature see Holzer (1991), Kain (1992), and Ihlanfeldt and Sjoquist (1998). All three reviews conclude that the SMH is supported by existing evidence.

[3] Focusing on youth is not above reproach. If children share behavioral characteristics with their parents (either due to nature or nurture), omitted productivity characteristics in equations estimated for youth may still be correlated with measures of neighborhood job opportunity.

[4] Although the emphasis of these studies is on the SMH, they also provide evidence on the NEH.

include dummy variables for three age categories, whether the recipient had less than a high school degree, the number of people in the household (three or fewer, six or more), and county of residence. Neighborhood effects are measured by the poverty rate of the recipient's census tract. Two job accessibility variables are included together in all estimated models – the total number of nearby jobs per adult in 1997 and the change in the latter variable between 1992 and 1997. From their results Allard and Danziger conclude that improvements in job access increase the employment of TANF recipients; however, there are some inconsistencies in their estimates. While their access variable based on employment levels is positive and statistically significant for both whites and nonwhites, their job change based measure of access is positive and significant only for whites. For nonwhites it is insignificant for the June 1996 snapshot and negative and significant for the 1998 snapshot. For reasons outlined below, job access for welfare recipients is best measured using job changes rather than job levels. Hence, this racial difference in their results is perplexing. One possible explanation, however, is that white welfare recipients have relatively greater residential choice, because they encounter less discriminatory treatment in the housing market. This greater choice may result in self-selection causing a larger upward bias in the estimated effect of job access for whites in comparison to nonwhites. Their neighborhood effects indicator (poverty rate of the census tract) has the expected negative effect on employment and is statistically significant in three of their four regressions, but the effect is inexplicitly positive and significant for nonwhites in 1996.

The second SMH study that focuses on TANF recipients is by Bania et al. (2003), who estimate logit employment models that are similar to those estimated by Allard and Danziger. As is true for the latter authors, Bania et al. use administrative data on TANF recipients (in their case for Cuyahoga County (Cleveland), Ohio for the year 1996), but their job location data are obtained from the U.S. Census Bureau's data file County Business Patterns. Their measure of neighborhood effects is again the poverty rate of the recipient's census tract. Job access is measured as the number of projected entry-level jobs that could be reached in a 20 minute commute by car or a 40 minute commute by public transit, with recipients assigned one of these two values depending upon whether they possessed a driver's license. Control variables included the type, if any, of housing assistance being given to the recipient along with a set of demographic variables. No variable on the educational level of the recipient is included because this information was not available.

Bania et al. find that the employment probability of TANF recipients is not affected by either job access or the neighborhood poverty rate. Moreover, job access (but not the poverty rate) is also statistically insignificant in their models explaining the recipient's level of (and change in) quarterly earnings.

Turning next to the NEH literature, the same problem that has plagued empirical investigations of the SMH – namely, endogenous residential location – limits what can be learned from existing studies.[5] Moreover, we found no NEH studies that have focused on the employment of TANF recipients.[6] The only evidence on neighborhood effects is therefore limited to what was reported above for the two SMH studies on TANF recipients.

The final literature that is relevant to our research are the studies based on the U.S. Department of Housing and Urban Development's demonstration "Moving to Opportunity" (MTO). In MTO public housing residents with children were eligible to participate in a lottery that randomly assigned them to one of three groups – a control group (remained in public housing), a Section 8 group (given a Section 8 voucher, without a location restriction), and an experimental group (received a Section 8 voucher that required finding housing within a census tract with low poverty (i.e., less than 10 percent)). While MTO was not limited to TANF recipients, a majority of the participants were receiving welfare at the time of assignment. The motivation behind MTO was that its randomized design would minimize bias resulting from the

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[5] For a review of the empirical evidence on the NEH, see Ihlanfeldt (1999).
[6] There are, however, two studies that have studied the influence of neighborhood residence on the probability of receiving welfare (Osterman, 1991; Vartanian, 1992).

self-selection of residential location. Results measured two years (Katz et al., 2001) and five years (Kling et al., 2004) after program entry show no statistically significant differences in employment or earnings between the control and experimental groups. These results suggest that nothing about place has an important effect on the labor market outcomes of housing assistance recipients.[7] However, Kling et al. acknowledge that moving to a low poverty neighborhood may not always improve job accessibility. Hence, the MTO results are more damaging to the NEH than they are to the SMH (to the extent that the neighborhood poverty rate captures neighborhood effects).

In summary, only two studies have specifically addressed the importance of space in affecting the employment probability of TANF recipients. Both studies ignore self-selection of residential location. In addition, neither study controls for access to childcare, and only one of the two studies includes the education attainment of the recipient as an explanatory variable. The MTO has the advantage of addressing self-selection via random assignment, but it provides no direct evidence on the effect that job access has on TANF recipients' employment probability. Below we describe the models that we estimate, which address each of the above criticisms of earlier work.

3. Data

To construct our panel of the quarterly employment experience of TANF recipients, data were assembled from a variety of sources: The Georgia Department of Labor, the Georgia Department of Human Resources, and the U.S. Census Bureau. Geographic data were obtained using the Maptitude Geographic Information System, and from the Environmental Systems Research Institute. The panel includes all females living in the Atlanta MSA who were TANF case heads and 15 to 65 years old in the first quarter of 1999. Individuals were followed over 16

[7] There were, however, significant differences between the control and experimental groups (that favored the experimental group) in measurements of the health of both adults and children.

quarters – from the first quarter of 1999 to the fourth quarter of 2002, regardless of whether they subsequently left welfare.[8] For the 13,679 individuals included, quarterly data are available for an average of 15.7 quarters, resulting in a total of 215,255 observations. The racial breakdown of the recipients is 11,597 nonwhites and 2,082 whites.[9]

3.1 Description of Variables

The variables comprising our panel are listed in Table 1 and are categorized in the table as dependent variable, individual characteristics, childcare accessibility, neighborhood and transit variables, accessibility measures to job growth and competing labor supply, and other controls. The individual variables included in each of these groups are described in turn below.

Our dependent variable is the full-time employment status of each individual for each quarter. Because hours worked are not available, quarterly wages are used to define full-time workers.[10] A large proportion of the TANF case heads reported less than $100 in quarterly wages, indicating that these individuals were only marginally employed in the formal labor market. For this reason full-time employment status is used as our dependent variable rather than whether any work occurred. Working full-time is defined as earning a minimum of $2,000 per quarter. This amounts to 30 hours per week at a real wage of $5.15 assuming a quarter length of 13 weeks.

Individual characteristics include age, age squared, whether the recipient graduated from high school, number of children under the age of 18, and whether welfare benefits had

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[8] Our panel begins in 1999 because the educational level of the recipient is not available for earlier years. The TANF data were provided by the Georgia Department of Human Resources.

[9] Nonwhites in Atlanta are overwhelmingly African-Americans: according to the 2000 Census, 77% of nonwhites are non-Hispanic African-Americans.

[10] Earnings data are obtained from the Individual Wage File collected by the Georgia Department of Labor, which contains quarterly wage information for all "covered" employees in the state of Georgia. A covered employee is defined as an employee for whom unemployment insurance is collected. The Individual Wage File also contains the ES202 employer identification number of the firm for which each individual works. The Individual Wage File is linked to the TANF administrative data via the social security number.

been received for eight consecutive quarters prior to the first quarter of 1999 (*Longterm*).[11] The probability of full-time employment is expected to be higher for older, and therefore more experienced individuals and for those with a high school degree. *Longterm* is included to account for unobserved individual characteristics, such as the individual's mental and physical health, that may reduce her employment probability. Because of their greater family demands, TANF recipients with more children are expected to be less likely to obtain or maintain full-time employment.

Childcare accessibility is measured by two variables – one to account for access to formal childcare (*Ccemp*) and the other to account for the availability of informal childcare (*Informal*). *Ccemp* equals the number of childcare workers working in the individual's neighborhood.[12] Although there are inherent difficulties in measuring the availability of informal childcare provided outside the household, the potential availability of informal childcare within the household is likely best measured by the presence of other adults within the household, since this allows for task specialization. *Informal* therefore registers whether there are two or more adults in the case.[13]

The neighborhood and transit variables include the poverty rate of the individual's block group (*Povrate*), whether the individual resides within a quarter of a mile of a transit line (*Transitqm*), and whether the individual lives in public housing (*Pubh*). Following Allard and Danziger and Bania et al., we use the poverty rate to measure neighborhood effects. [14,15] Public

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[11] Individual and case-level characteristics of TANF recipients, including addresses, are obtained from the TANF administrative data that are collected by the Georgia Department of Human Resources.

[12] For *Ccemp* and all other neighborhood variables the census block group is used as the neighborhood unit. *Ccemp* is constructed from the file ES202 Firm-Level Employment Data, which was provided by the Georgia Department of Labor. This file contains 4-digit Standard Industrial Classification (SIC) numbers identifying the specific industry of the firm along with quarterly employment levels and the establishment address.

[13] While other adults in the household may be a source of informal childcare, they may also require care themselves, especially if they are elderly. We do not expect however, that this situation arises so frequently that it undermines the usefulness of *Informal* as a measure of access to informal childcare.

[14] Unlike these earlier studies, however, we use the block group rather than the census tract as the neighborhood. Because of Atlanta's relatively low population density, census tracts are large even within

transit is considered accessible if it is within a quarter mile, because evidence indicates that most people will not use transit if they must walk a longer distance (Bernick and Carroll, 1991; Cervero, 1994; Untermann, 1984).[16] The dummy variable for public housing residents is included because for them the relevant neighborhood is best described as the project itself rather than the entire block group.

A central focus of our study is to determine whether the TANF recipient's proximity to job opportunity affects her probability of full-time employment. The job opportunity afforded to a TANF recipient living in a particular neighborhood depends on the number of nearby job vacancies (henceforth referred to as job access) in comparison to the number of workers competing for these vacancies (henceforth referred to as the competing labor supply). The maximum commuting area of the TANF recipient is assumed to be larger than the home neighborhood but smaller than the entire metropolitan area; hence, job opportunity varies across neighborhoods.

Ideally, data on job openings by skill level and location would be available for constructing the job access measure. In the absence of such data, we draw upon internal labor market theory to justify using the quarterly change in jobs to identify jobs suitable for welfare recipients.[17] Internal labor markets refer to the practice of firms filling more skilled positions from within the ranks of current employees in order to minimize hiring costs. Hiring done outside the firm is only a certain low-level "points of entry".[18] To account explicitly for distance

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the central city (on average 1.22 square miles). Block groups therefore represent a more meaningful spatial unit for defining what most people think of as a neighborhood.

[15] The unemployment rate, labor force nonparticipation rate, and racial composition of the neighborhood were also used to measure neighborhood effects. Due to their co-linearity with the poverty rate and general lack of statistical significance, these variables were ultimately dropped from the analysis. All census block group variables come from the 2000 Census of Population.

[16] The public transit variable is constructed from public transit base maps, along with a geographic information system.

[17] The quarterly change in jobs is measured at the block group level using the ES202 data set described above.

[18] Our job access variable is also based on Raphael (1998), who concludes after empirical experimentation with alternative job access variables that those based on employment change are superior

in our job access measure, more distant job changes are discounted using a distance decay function:

$$ACCESS_i = \sum_{j=1}^{j=J} CHANGE_j * exp(-\gamma d_{ij}), \quad (1)$$

where $CHANGE_j$ represents the growth in the number of jobs from the previous quarter in block group j; d_{ij} is the distance in miles between the centroids of block groups i and j; and γ is the "distance-decay" function.[19] ACCESS is a gravitational potential measure of proximity (Isard, 1960) that places less weight on relatively distant employment opportunities. Weighting opportunities by distance is based on the assumptions that information on jobs declines with distance and that workers base their employment decisions on offer wages net of commuting costs.[20]

ACCESS captures spatial variation in the demand for labor, but it does not account for geographical variation in labor supply. The latter is important to measure because TANF recipients are concentrated in areas that tend to be densely populated with individuals who, like themselves, are relatively undereducated and therefore potential competitors for available jobs. To measure competing labor supply, we employ the same distance-decay function as before:

$$LFCOMPETE_i = \sum_{j=1}^{j=J} SUPPLY_j * exp(-\gamma d_{ij}), \quad (2)$$

where $SUPPLY_j$ equals the number of adults living in block group j possessing no more than a high school degree.

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to those based on employment levels in explaining inter-neighborhood differences in youth employment rates.

[19] ACCESS uses an exponential deterrence functional form based on Isard et al. (1998), who conclude that this form is superior to the power function when focusing on commutes or relatively short distances. After experimentation with a range of values, $\gamma = 1$ was selected because it provided the greatest explanatory power. However, our conclusions regarding the importance of job access to employment probability are not dependent on the choice of γ.

[20] ACCESS is also computed separately for each major SIC grouping. As reported below, separate models are estimated using the all-jobs ACCESS variable and ACCESS variables broken down by industry group.

The additional control variables entering our models include dummy variables for time period (year-quarter) and for the recipient's county of residence. In Georgia TANF is administered at the county level; hence, differences in employment probability may exist across counties due to differences in program administration (e.g., some counties may provide more help than others to the recipient in her search for a job). The Atlanta MSA contains 20 counties, with Fulton County being the central county. Preliminary runs including a full set of county variables (Fulton is the reference) revealed that for nonwhites county effects are accounted for by including dummy variables for the inner suburban counties of Clayton and Dekalb and dummy variables grouping the 17 remaining counties into those south (8 counties) and north (9 counties) of Interstate 20. For whites, Fulton (again the reference) and Clayton Counties are separately represented, but Dekalb is included among the southern counties.

Table 1 also distinguishes the variables that are time-varying from those that are time-constant. Intertemporal variation in the time-varying variables comes from variation without the recipient moving in the case of *Age*, *Children*, *Ccem*p, *Informal*, *Access*, and *Lfcompete*. Variation in the latter four variables also comes from relocation. For the variables *Povrate* and *Pubh* variation comes only from relocation. The time-constant variables are *Hsgrad* and *Longterm*.

3.2 Summary Statistics

Table 2 contains summary statistics for all of the variables broken down by the race of the recipient. On average, about 25 percent of the recipients are employed full time during any given quarter, regardless of race. The typical recipient is nonwhite in her middle thirties and lacks a high school diploma. Half of the whites and 67 percent of the nonwhites are long-term recipients of welfare benefits. Family structure also differs between the races, with nonwhites having on average .5 more children than whites. There is, however, little difference in the proportion of cases with two or more adults present in the household.

The residential locations of nonwhites and whites are markedly different. Nonwhite recipients are much more centrally located, with 62 percent living in the central county in comparison to only 10 percent of the whites. Given their centralization, it is not surprising that the neighborhoods of the nonwhites are characterized by inferior job access, greater competition for jobs, and a higher poverty rate (almost three times higher). Nonwhites are also about four times more likely to live in public housing than whites. However, the neighborhoods of nonwhites do offer two advantages over those occupied by whites – access to childcare and to public transit are better in the nonwhites' neighborhoods.

4. Empirical Methodology

We explain the employment status of individual TANF recipient *i* during quarter *t* in terms of job accessibility, labor market competition, neighborhood characteristics, and individual characteristics. The generic model for employment choice is specified as

$$E_{it}^{*} = Z_{it}\beta_1 + L_{it}\beta_2 + A_{it}\beta_3 + C_{it}\beta_4 + G_{it}\beta_5 + W_{it}\beta_6 + \nu_i + \varepsilon_{it}, \tag{3}$$

$$(i = 1,...N;\ t = 1,\dots,T;\ n = NT)$$

$$E_{it} = \boldsymbol{I}(E_{it}^{*} > 0), \tag{4}$$

where E_{it}^{*} is the latent variable reflecting the benefits of full time employment; E_{it} is a *0-1* dummy variable with ***1*** indicating the individual is employed full time; the vector *Z* consists of the set of individual- and case-level (family) characteristics; *L* is the measure of labor market competition from (2); *A* denotes either a single aggregate measure of job access or a vector of industry-based measures of access constructed as in (1); *C* are the childcare accessibility variables; *P* is the neighborhood poverty rate; and *W* is a vector of other control variables, including access to public transit, county effects, and calendar time effects. Here, $\beta = \left(\beta_1',...,\beta_6'\right)'$ denotes a vector of unknown parameters associated with $X_{it} = \left(Z_{it},...,W_{it}\right)$.

The ν_i are the individual effects which reflect unobserved recipient-specific characteristics, and ε_{it} are the typical error terms.

To estimate (3), we employ a version of Chamberlain's random effects probit model (CRE) that allows unobserved effects to be correlated with all of our time-varying independent variables.[21] Specifically, it is assumed that ν_i is related to elements of X_i by

$$\nu_i = \varphi + \overline{X}_i \alpha + \eta_i, \tag{5}$$

where $\overline{X}_i = \frac{1}{T}\sum_{t=1}^{T} X_{it}$ and η_i, conditional on X_i, is distributed as normal $(0, \sigma_\eta^2)$.[22] The random component ε_{it}, conditional on both X_i and ν_i, is assumed to follow the normal distribution. The primary advantage of our CRE model is that by allowing ν_i and the place-based variables to be correlated, we are controlling for the self-selection of residential location.

In addition to unobserved individual effects, current employment may depend on the TANF recipient's past employment experience. To the extent that search costs are involved in labor force participation and employment opportunities differ according to the individual's employment status, the TANF recipient's labor force participation decision may depend on her previous employment experience. We therefore also estimate a dynamic model of employment choice that allows for state dependence:

$$E_{it}^* = \rho E_{it-1} + Z_{it}\beta_1 + L_{it}\beta_2 + A_{it}\beta_3 + C_{it}\beta_4 + G_{it}\beta_5 + W_{it}\beta_6 + \nu_i + \varepsilon_{it}, \tag{6}$$

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[21] For discussion of CRE and related models see Hsiao (2003). An alternative estimator of (3) is the fixed effects logit model. This estimator assumes that employment outcomes $E_i = (E_{i1} \ldots E_{iT})$ are independent conditional on the observed and unobserved characteristics $X_i = (X_{i1} \ldots A_{iT})$ and ν_i. We chose not to use this model because it only estimates the effects of time-varying explanatory variables and does not allow for the estimation of partial effects. The model also results in loss of information because individual observations with the same employment experience overtime (*e.g.*, recipient employed during all quarters) do not contribute to the estimation.

[22] As noted in the previous section, a number of our independent variables are time-constant. While these variables can be included in our models, we cannot distinguish their effects from ν_i unless we assume that ν_i is uncorrelated with these variables.

$$E_{it} = \boldsymbol{I}(E_{it}^{*} > 0)$$

$$(i = 1,...N;\ \ t = 1,\ldots,T)$$

where E_{it-1} is the participation state variable and ρ is the state dependence parameter. The estimation of model (6) requires specification of the error components and the initial conditions of the dynamic process. Using the probit specification, we have

$$\begin{aligned} &P\left(E_{it} = 1 \mid E_{it-1},...,E_{i0},X_i,\nu_i\right) \\ &= \Phi\left(\rho E_{it-1} + Z_{it}\beta_1 + L_{it}\beta_2 + A_{it}\beta_3 + C_{it}\beta_4 + G_{it}\beta_5 + W_{it}\beta_6 + \nu_i\right) \\ &= \Phi\left(\rho E_{it-1} + X_{it}\beta + \nu_i\right), \end{aligned} \tag{7}$$

where $\Phi(a)$ denotes the standard normal distribution function, evaluated at a.

In order to estimate (7), we adopt the dynamic nonlinear random effects approach recently proposed by Wooldridge (2005). The approach provides practical solutions to the initial conditions problem in nonlinear individual effects models. In particular, in the context of dynamic probit with unobserved heterogeneity, the estimation method provides a strategy for computing average partial effects.

Analogous to specification (5), the random effects are assumed to be normally distributed, conditional on a linear function of the explanatory variables and the initial employment state, E_{i0}. In particular,

$$\nu_i = \varphi + \gamma E_{i0} + X_i\alpha + \eta_i, \tag{8}$$

where $\eta_i \mid \left(E_{i0}, X_i\right) \sim N\left(0,\sigma_\eta^2\right)$. The initial time period $t = 0$ corresponds to 1999:Q1 so that the initial fulltime employment status dummy is E_{i0}. The ensuing mixture density of $\left(E_{i1},...,E_{iT}\right)$ given $\left(E_{i0},X_i\right)$ provides the basis for maximum likelihood estimation of the unknown parameters; see Wooldridge (2005) for further details.[23]

[23] In implementation, we employ 12 to 16-point Gauss-Hermite quadrature, and determine that the quadrature procedure is stable in our application.

In our dynamic probit model we allow v_i to be correlated with *Lfcompete*, *Access*, and *Informal* in all time periods. For the other time-varying variables v_i depends on the over time mean.[24]

The average partial effects are based on the estimator of

$$\mathrm{E}\left[\Phi\left\{\left(\rho E_{it-1}+X_{it}\beta+\varphi+\gamma E_{i0}+X_i\alpha\right)\cdot\left(1+\sigma_\eta^2\right)^{-1/2}\right\}\right], \tag{9}$$

where expectation is taken with respect to the distribution of $\left(E_{i0}, X_i\right)$. We follow Wooldridge (2005) and replace the expected value in (9) with the sample average over individuals, evaluated at the parameter estimates.

Consistent estimation of the above models requires the assumption of strict exogeneity of the regressors (Wooldridge 2002). This assumption is violated if employment status has an effect on current or future values of the explanatory variables. One possible source of reverse causation is that having a job may cause some recipients to move to get closer to work. If this is the case then estimates of the effect of job access on employment probability will be upwardly biased. This represents a second type of bias that results from the self-selection of residential location. Recall from above that the first type we have identified occurs when unobserved individual effects affect both residential location and employment. One approach toward a complete attenuation of both types of selection bias is to use a subsample of recipients whose locations are randomly assigned and who are unlikely to move to get closer to work. Such a subsample is formed by using only those recipients living in public housing. Individuals who apply for public housing are assigned to their units based upon the housing requirements of their families and current availability. There is therefore minimal self-selection. In addition, once an

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[24] We do not allow v_i to depend on all of the time-varying variables in all time periods in order to conserve on degrees of freedom. However, our results are unchanged if v_i is allowed to be correlated in each time period with variables other than *Lfcompete*, *Access*, and *Informal.*

individual acquires a public housing unit she is unlikely to sacrifice the unit in order to get closer to work.

Estimation is carried out for public housing residents as well as for the regular sample of TANF recipients. Models are estimated separately by race, nonwhites and whites. The sensitivity of the results to different specifications of the control variables and to different panel data estimators is explored.

5. Estimation Results

This section presents the results from estimating various specifications of the static probit model that allows for individual effects but no state dependence and the dynamic probit model, which incorporates state dependence for employment status as well as individual heterogeneity. The dependent variable is a binary variable indicating full-time employment status as defined earlier in Section 3.

Tables 3 and 4 present sets of estimates from the CRE and dynamic probit models, respectively. Note that Table 3 contains the names of the explanatory variables (e.g. *Access*) and the variable names with the letter "*b*" appended (e.g., *Accessb*). Table 4 also contains *b* appended variables, but for select variables (*Lfcompete, Access*, and *Informal*) variable names appear which are appended with numbers (*e.g.*, *Access1* – *Access15*).[25] The estimated coefficient reported for an appended variable name allows for correlation between the unobserved individual effect (v_i) and the variable. Those appended with a *b* allow correlation between v_i and the over time average of the variable. Those appended with the numbers 1 to 15 allow correlation between v_i and the variable in all time periods.[26] As noted above, in the CRE models we allow v_i to be correlated with the over time mean of each of the time-varying

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[25] Complete sets of results for the dynamic probit models are reported in Appendix Table A1.
[26] The estimated coefficients on these variables also enter the formula used to calculate average partial effects, see (9) and (10).

explanatory variables. In the dynamic probit models we allow ν_i to be correlated with *Lfcompete*, *Access*, and *Informal* in all time periods. For the other time-varying variables ν_i depends on the over time mean. Although we present the CRE probit estimates for comparison, in our discussion of the results we highlight those obtained from the preferred dynamic probit model..[27]

The results show that employment participation is characterized by highly significant positive state dependence (its magnitude is considered below) and unobserved heterogeneity. In all CRE and dynamic probit specifications, the variance of the individual effect is tightly estimated. Allowing for state dependence has a substantial effect on the estimated unobserved heterogeneity: on average, the proportion of the total variance due to the individual effect (labeled τ in the tables) falls from about 0.75 in the CRE model to about 0.45 in the dynamic probit model. The results from the dynamic probit model show that the initial employment status is also quite important, and implies that there is significant correlation between recipient-specific unobserved heterogeneity and the initial employment condition.

The estimated coefficients on the appended variable names reveal that a number of the place-based variables have statistically significant correlations with ν_i. These include *Povrate* and *Access* in the CRE models and *Access* in the dynamic probit models for both whites and nonwhites. These results underscore the importance of controlling for the self-selection of residential location in testing the SMH and NEH as they apply to TANF recipients.

Estimation results also demonstrate a substantial difference between nonwhite and white recipients with regard to the effects of the independent variables in this large urban area. Next, we discuss the effects of each group of independent variables on participation in fulltime employment.

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[27] Estimation results from dynamic probit are based on balanced panel data of 15 quarters, 1999:Q2 – 2002:Q4. The initial time period $t = 0$ corresponds to 1999:Q1, with initial employment status E_{i0} denoted by *Ftemploy0* in the tables.

Individual Characteristics

TANF recipients with more children are expected to be less likely to obtain or maintain full-time employment because of family demands or negative workforce characteristics associated with dependent family members (e.g., increased worker absenteeism). Estimates from the dynamic and CRE probit specifications indicate that both whites and nonwhites have a lower probability of full-time employment as the number of children in the household increases, and the estimated effects are significant at the .05 level; however, the effect is substantially larger for whites than for nonwhites.

Age and its square are included to proxy for experience.[28] The expectation is that, as the individual ages, she gains experience and is more likely to be employed. For non-whites in the CRE specification, coefficients on *Age* and *Agesquared* have the expected signs and are statistically significant; however, the effects of age on the probability of full-time employment have statistically insignificant effects for both whites and nonwhites in the dynamic probit model.

All that is known about the educational attainment of the recipient is whether or not she completed high school. The results show that both whites and nonwhites that completed high school are more likely than non-completers to be employed full-time, with each of the effects significant at the .01 level in the dynamic probit model.[29]

The binary variable *Longterm* is included to account for unobserved negative individual characteristics that may affect employability. The estimated effect of *Longterm* is consistently negative and significant for both whites and nonwhites. The strong, negative effects of *Longterm* indicate that unobserved characteristics related to longer welfare spells do reduce the probability of employment. These results also underscore the importance of unobserved

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[28] For the dynamic probit model, we include age of the welfare recipient in 1999 quarter 2.

[29] Because education is a time-constant variable in our models, care should be taken in interpreting its estimated effect. As noted above, to distinguish its effect from ν_i the assumption is required that the two variables are independently distributed.

individual heterogeneity in explaining differences in the employment probability of the recipients.

Childcare Accessibility

Access to informal childcare (*Informal*) is positive and statistically significant for both whites and nonwhites in the CRE models, but is significant for only nonwhites in the dynamic probit. However, the interaction between informal childcare access and the number of children is statistically significant for whites in the dynamic probit model, which indicates that with more children having two or more adults in the household increases the probability of full-time employment. In contrast to the results obtained for *Informal*, access to formal childcare within the home neighborhood (*Ccemp*) is never significant in any of the models.

Neighborhood and Transit Variables

As in prior studies, we measure neighborhood effects by including the poverty rate of the recipient's neighborhood as a regressor. In all cases, the estimated effects are statistically insignificant.[30] It is worth noting that we obtain very different results from estimating a cross-sectional model. Using the values of all of the variables for the first quarter of 2001, probit model estimates show that the neighborhood poverty rate has a negative and highly significant effect on the full-time employment probability of both whites and nonwhites. The contrasting results obtained from the cross-sectional models in comparison to those yielded by our panel data models suggest that ignoring the self-selection of residential location causes biased estimates of the importance of neighborhood effects on the probability of employment.

The other variables included in this group of variables are dummy variables indicating whether the recipient lives in public housing and whether she resides within a quarter mile of a

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[30] In their review of the neighborhood effects literature, Ellen and Turner (1997) note that a number of studies have found that the neighborhood poverty rate only affects individual behaviors above a certain threshold. This threshold is commonly defined as a poverty rate of 40 percent. We therefore also ran our models with a dummy variable for whether the neighborhood poverty rate exceeded 40 percent. This variable is also not significant in any of the cases.

public transit line. Neither of these variables is found to affect the employment probability of either whites or nonwhites. We also tried interacting the transit and job access variables, based on the expectation that transit matters more when commutes are shorter. These interactions are also not significant. Our public transit results have a direct bearing on the debate surrounding the transportation needs of welfare recipients.

The U. S. Department of Housing and Urban Development recently completed its "Bridges to Work" (BTW) demonstration project (Roder and Scrivner, 2005). This project was designed to connect inner-city job seekers to suburban jobs by providing improved public transportation services to project participants. Comparisons between the labor market outcomes of workers randomly assigned to experimental and control groups revealed that these transportation services had no effect on earnings or employment. This held true for low-skilled workers generally and for those participants who were TANF recipients. These findings are consistent with our results showing that having public transit within walking distance does not increase employment probability. Surveys conducted with the BTW participants indicated that the transportation services failed to improve outcomes because commuting times were intolerably long. An unresolved question is whether shorter commutes would result in improved transportation making a difference. The insignificance of our interaction variables support a "no" answer to this question.

Another finding of BTW is that having a driver's license is associated with greater wages and annual earnings. This same result is reported by Bania et al. (2003), who find a license improves both the earnings and employment of Cleveland's TANF recipients. While the direction of causality is unclear, these findings when combined with ours suggest that TANF recipients may need more flexible transportation than that provided by public transit in order to meet both their childcare and work requirements.

Job Accessibility and Competing Labor Supply

As anticipated, the estimated coefficients on our measure of job accessibility (*Access*) are in all cases positive. In the CRE models, the *Access* coefficient is statistically significant at .10 level for nonwhites, but it is not significant for whites. Neither of the coefficients is significant in the dynamic probit models at conventional levels by a two-tailed test. However, we have a clear sign hypothesis (+) for the *Access* variable; hence, it is worth noting that for nonwhites it is statistically significant at the .10 level using a one-tailed test. Our measure of the competing labor supply (*Lfcompete*) is also never significant using a two-tailed test, but it is negative (as expected) and significant at the .10 level for whites in the dynamic probit model by a one-tailed test.

Models were also estimated with *Access* measured separately for the four industry groups most likely to hire TANF recipients – Finance, Insurance, and Real Estate (FIRE), Retail, Services and Manufacturing.[31] For nonwhites these variables are never statistically significant. The results for whites, once again, underscore the importance of controlling for the self-selection of residential location. Proximity to retail jobs consistently has a positive effect on the employment probability of whites, but the significance level of this effect declines as better control is obtained for individual unobserved heterogeneity. Retail access is significant at the .05 level in a simple cross sectional model, at the .10 in the CRE model, and at the .35 level in the dynamic probit model.

Estimated Average Responses

To illustrate the magnitudes of employment responses to changes in job accessibility, childcare, number of children and state dependence, we report the estimated average partial

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[31] The industry groups most likely to hire welfare recipients were determined by using the Public Use Micro-data Sample for the Atlanta MSA to estimate the percentage of the jobs within each major industry group held by welfare recipients.

effects.[32] From equation (9), the estimated APEs can be obtained by averaging out unobserved heterogeneity ν_i:

$$\frac{1}{N}\sum_{i=1}^{N}\left[\Phi\left\{\left(\hat{\rho}E_{it-1}+X_{it}\hat{\beta}+\hat{\varphi}+\hat{\gamma}E_{i0}+X_i\hat{\alpha}\right)\cdot\left(1+\hat{\sigma}_{\eta}^{2}\right)^{-1/2}\right\}\right], \tag{10}$$

where parameters have been replaced with their maximum likelihood estimates and again E_{it} denotes $Ftemploy_{it}$.

The average partial effects for selected periods are shown in Table 5, broken down by race and key time-varying explanatory variables. The estimate of state dependence is substantial for both whites and nonwhites. As compared to a case head not employed full-time in the previous quarter, for a TANF case head fully employed in the last quarter, the estimated increase in the probability of being employed in the current quarter is about .32 regardless of race.

The average response to an additional child is about -.01 for whites and -.004 for nonwhites. The availability of informal childcare increases the probability of full-time employment by about .06 for nonwhites and .03 for whites. Increasing job accessibility by one standard deviation raises the probability of employment by about .002 for both racial groups. For whites, an increase of one standard deviation in our measure of the competing labor supply decreases the probability of employment by about .02. Generally, the average responses are remarkably similar over time.

6. Results for Public Housing Residents

Table 6 gives summary statistics for the subsample of nonwhite TANF recipients residing in public housing.[33] Because public housing within the Atlanta MSA is highly concentrated within the central county, only a dummy variable for Fulton County is included to

[32] APEs can only be estimated for time-varying variables. We only report APEs for those variables that are statistically significant (or approach significance) at conventional levels.
[33] There are too few observations of white residents in public housing for meaningful estimation.

control for county effects. As compared to the overall nonwhite sample of TANF recipients, the public housing residents are younger, have more children, fare worse in terms of employment and educational attainment, and are more likely to be long-term welfare recipients.

The evidence presented in Table 4 for all nonwhite recipients provides weak support for the SMH in that *Access* is statistically significant by a one-tailed test. However, we have noted that this estimate may be upwardly biased if recipients with jobs move closer to where *Access* is higher in order to reduce the length of their commutes. Given the excess demand and correspondingly long waits that exist for public housing apartments, we expect that recipients with jobs living in public housing will not sacrifice their apartments in order to get closer to work. Hence, there should be no upward bias in the estimated effect of *Access* for public housing residents.

Table 7 gives results for the nonwhite TANF recipients living in public housing using the CRE model (first two columns) and the dynamic probit model (last two columns). In both models *Access* is less statistically significant than in the models estimated for the full sample of recipients. Most importantly, it is highly insignificant in the dynamic probit model.[34]

The rest of the results for the public housing residents mirror those obtained for the full sample: 1) state dependence, initial employment status, and unobserved heterogeneity are statistically significant, and 2) *Informal*, *Longterm*, and *Hsgrad* again all have strong effects on employment probability. There are two cases where the results do differ – 1) the age variables are significant for the public housing residents but are not significant for the full sample, and 2) the number of children is not significant for the public housing residents, but it is negative and significant for the full sample.

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[34] It is curious, however, that the results also show that *Access* is correlated with v_i. This is not expected if location assignments are truly random. In fact, assignments depend on family size, which may cause some correlation between *Access* and v_i if larger apartments are not spatially random.

Table 8 gives average partial effects for the nonwhite recipients living in public housing. The APEs of *Lfcompete* and *Children* are not reported since the underlying coefficient estimates are highly insignificant.[35] The estimated effect of state dependence (about .29) is slightly less than in the dynamic model estimated for the full sample. For *Informal*, the estimated increase in employment probability of about .067 shows that nonwhite public housing residents are approximately 0.5% more likely to be employed full-time in the presence of informal childcare than are nonwhites in the full sample of TANF recipients. A one standard deviation increase in job access increases the probability of employment by about .001, which is roughly in line with the APE estimated for the full sample.

7. Conclusions

In recent years, the role that intra-metropolitan residential location plays in explaining the relatively low earnings and employment of minorities has been hotly debated. The two main hypotheses that relate location to economic opportunity are the spatial mismatch hypothesis and the neighborhood effects hypothesis. Based on the evidence that had accumulated over the years supporting these hypotheses, it was generally felt space would have a strong effect on welfare recipients' labor market outcomes. However, recent studies that have focused specifically on TANF recipients have produced results that fail to provide much support for either the SMH or the NEH. Two of these studies (Allard and Danziger, 2002; Bania et al., 2003) rely upon non-experimental methods, while the MTO demonstration is based on a random assignment experiment. A limitation of the non-experimental studies is that they ignore the self-selection of residential location. While the MTO is specifically designed to handle this issue, the treatment is the neighborhood poverty rate and not job accessibility.

[35] Although not significant, we report an APE for job access so its magnitude can be compared to the APE estimated for the full sample.

In this paper we have exploited a unique panel of the quarterly employment experiences of TANF recipients living within the Atlanta MSA. Our data allowed us to estimate dynamic discrete choice specifications of the full-time employment decisions of the recipients. The estimated models provide strong control for unobserved individual effects. Moreover, even stronger control for these effects is provided by the models we estimate for TANF recipients residing in public housing. We find strong evidence of positive state dependence and unobserved individual heterogeneity.

For both white and nonwhite recipients we find little support for either the SMH or the NEH. While space may matter to other disadvantaged workers, it does not seem to be important to the employment probability of welfare recipients. What does seem to matter, according to our results, are the individual and family characteristics of the recipient, both observed and unobserved. The observed variables that matter are the age and education of the recipient and the number of children and adults in her family. The strength of the effects estimated for unobserved individual heterogeneity, initial employment status, and long-term usage of public assistance underscore the importance of unobserved individual characteristics on employment probability.

While we find no evidence in support of space as an important determinant of recipient employment, our results should not be construed to imply that space is inconsequential to the overall well-being of the recipient. In addition to possibly beneficial non-employment effects, neighborhoods with less poverty and nearby job opportunities may provide long-run improvements in employment probability not captured by our results.

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Table 1: List and Description of Variables Used in Estimation of Employment Choice of TANF Recipients	
Variable	**Description**
Dependent Variables	
*Ftemploy**	= 1 if employed full time; 0 otherwise
Individual Characteristics	
*Age**	Age in years
*Agesquared**	Age in years squared
Hsgrad	= 1 if TANF recipient graduated high school
Nonwhite	= 1 if TANF recipient is non-white
Longterm	= 1 if the TANF recipient has received benefits for 8 consecutive quarters prior to 1999 quarter 1
*Children**	Number of children under age 18 in the household
Childcare Accessibility	
*Ccemp**	The number of childcare workers in the home census block group
*Informal**	= 1 if there are two or more adults in the household (informal childcare availability)
Neighborhood and Transit Variable**s**	
*Povrate**	Poverty rate: Fraction of residents in the block group falling below the poverty line in 2000
*Transitqm**	= 1 if residing within a quarter mile of public transit line
*Pubh**	= 1 if public housing resident
Accessibility Measures to Job Growth and Competing Labor Supply	
*Access**	Proximity to job growth (see equation 1)
*Lfcompete**	Proximity to other individuals over 25 years old with high school diploma or less (see equation 2)
Other Controls	
*Clayton**	= 1 if TANF recipient is residing in Clayton county
*Dekalb**	= 1 if TANF recipient is residing in Dekalb county
*Fulton**	= 1 if TANF recipient is residing in Fulton county (reference)
*I20South**	= 1 if TANF recipient is residing in one of the counties south of I20 highway
*I20North**	= 1 if TANF recipient is residing in one of the counties north of I20 highway
Time effects	Dummy variables to control for calendar time effects (year-quarter)

* Denotes time-varying variables.

Table 2: Descriptive Statistics by Race (1999:Q1 to 2002:Q4 Unbalanced Panel)								
	White (Obs=32,288)[a]				Nonwhite (Obs = 182,967)[b]			
Variable	**Mean**	**Std. Dev.**	**Min**	**Max**	**Mean**	**Std. Dev.**	**Min**	**Max**
Dependent Variable								
Ftemploy	0.23	0.42	0	1	0.26	0.44	0	1
Individual Characteristics								
Age	38.43	11.48	16.19	64.99	35.27	10.70	16	65
Agesquared	1608.59	930.03	262.26	4223.22	1358.35	832.18	241.06	4223.93
Hsgrad	0.36	0.48	0	1	0.42	0.49	0	1
Longterm	0.52	0.50	0	1	0.67	0.47	0	1
Children	1.94	1.11	1	11	2.45	1.50	1	14
Access to Job Growth and Competing Labor Supply								
Lfcompete	2365.18	2120.64	28.52	11179.80	5952.88	2933.91	50.17	11200.31
Access	7.98	188.83	-4683.11	4399.13	-37.71	422.30	-4805.66	4894.26
Childcare								
Ccemp	8.05	17.77	0.00	163.67	8.37	17.59	0.00	164.67
Informal	0.54	0.50	0	1	0.49	0.50	0	1
Neighborhood and Transit Variables								
Povrate	0.11	0.09	0.00	0.71	0.30	0.21	0.00	0.77
Transitqm	0.14	0.35	0	1	0.74	0.44	0	1
Pubh	0.05	0.22	0	1	0.19	0.39	0	1
Counties								
Clayton	0.13	0.34	0	1	0.07	0.26	0	1
Dekalb					0.15	0.36	0	1
Fulton	0.10	0.30	0	1	0.62	0.48	0	1
I20South	0.32	0.47	0	1	0.07	0.25	0	1
I20North	0.42	0.49	0	1	0.08	0.27	0	1

[a] There are 2082 white TANF recipients observed for min=2 quarters, max=16 quarters and average of 15.5 quarters.

[b] For unbalanced panel data of nonwhites, there are 11,597 TANF recipients observed for a minimum of 2 quarters and maximum of 16 quarters, with average of 15.8 quarters per individual.

Table 3: Results from Chamberlain Random Effects Probit Model[a]				
	White (Obs=32288)		Non-White (Obs=182967)	
Variable	Coef	t-stat	Coef	t-stat
Age	-0.19034	-0.78	0.22707*	1.79
Agesquared	-0.00433***	-9.75	-0.00422***	-21.22
Hsgrad	0.06212	0.65	0.32682***	8.48
Longterm	-0.45715***	-4.71	-0.39776***	-9.62
Children	-0.12424***	-3	-0.03792***	-3.42
Lfcompete	0.00004	1.19	0.00000	0.73
Access	0.00009	1.31	0.00002*	1.79
Ccemp	-0.00123	-0.67	0.00074	1.27
Informal	0.44256***	6.5	0.75398***	30.41
*Informal*Children*	0.03308	1.19	0.01316	1.59
Povrate	-0.31879	-0.55	-0.05468	-0.53
Transitqm	0.12287	0.64	-0.05151	-1.01
Pubh	0.03813	0.19	0.0017	0.04
Clayton	0.14688	0.56	0.02662	0.34
Dekalb			-0.06468	-1.13
I20South	0.63820**	2.27	-0.32010***	-2.77
I20North	0.48702*	1.82	-0.16800*	-1.68
Ageb[b]	0.19818	0.81	-0.21500*	-1.68
Agesquaredb	0.00429***	7.57	0.00405***	16.04
Childrenb	-0.03033	-0.4	-0.05740**	-2.31
Lfcompeteb	0.00000	0.04	-0.00001	-0.94
Accessb	0.00222**	2.1	0.00074**	2.44
Ccempb	-0.00192	-0.57	0.00009	0.07
Informalb	-0.08952	-0.32	0.44405***	3.72
*Informal*Childrenb*	0.25282**	2.2	0.12817***	3.16
Transitqmb	-0.33055	-1.15	-0.07534	-0.8
Pubhb	0.00904	0.03	-0.11505	-1.48
Claytonb	-0.58600	-1.64	-0.17370	-1.37
Dekalbb			-0.17687**	-2.12
I20Southb	-0.99703***	-2.77	0.14744	0.94
I20Northb	-0.65344*	-1.93	-0.03532	-0.26
Constant	-2.88549***	-3.75	-2.33848***	-6.81
Sigma_ η (Standard Error)	2.00075	(0.044)	1.81321	(0.018)
τ	0.80012		0.76678	
Log likelihood	-9401.71		-59478.79	

* (**) [***] Statistically significant at the 10% (5%) [1%] level of significance.

(a) Includes controls for year-quarter effects.

(b) Individual effects are allowed to depend on overtime means of all time-varying explanatory, variables each suffixed by *b* in all tables.

Table 4: Results from Dynamic Unobserved Effects Probit Model (1999Q2 – 2002Q4)[a]				
	White (Obs=29055)		Non-White (Obs=168705)	
Variable	**Coef**	**t-stat**	**Coef**	**t-stat**
Ftemploylag	1.62937***	49.85	1.44756***	114.3
Age	-0.00224	-0.13	-0.00867	-1.24
Agesquared	-0.00013	-0.59	-0.00006	-0.67
Hsgrad	0.15145***	2.6	0.14468***	6.51
Longterm	-0.12732**	-2.09	-0.13327***	-5.5
Children	-0.11142**	-2.44	-0.02270**	-1.96
Lfcompete	-0.00007	-1.61	0.00000	0.09
Access	0.00008	1.16	0.00002	1.42
Ccemp	-0.00248	-1.14	0.00055	0.88
Informal	0.10662	1.39	0.38128***	14.32
*Informal*Children*	0.05905*	1.9	-0.00026	-0.03
Povrate	-0.34231	-0.5	-0.08939	-0.81
Transitqm	0.05753	0.26	-0.05909	-1.05
Pubh	0.04055	0.17	-0.00122	-0.03
Clayton	0.14545	0.47	0.02835	0.34
Dekalb			-0.00129	-0.02
I20South	0.12285	0.38	-0.29687**	-2.31
I20North	0.13085	0.43	-0.11504	-1.03
Ftemploy0	1.76830***	21.96	1.61747***	49.26
Childrenb	0.06301	0.88	-0.01339	-0.73
Ccempb	-0.00098	-0.35	-0.00098	-1.05
*Informal*Childrenb*	0.0181	0.2	0.06168**	2.41
Transitqmb	0.02137	0.08	0.04167	0.58
Pubhb	0.1146	0.4	0.01874	0.32
Claytonb	-0.27045	-0.78	-0.06012	-0.59
Dekalbb			-0.15282**	-2.15
I20Southb	-0.18888	-0.54	0.22011	1.54
I20Northb	-0.18672	-0.57	-0.08298	-0.67
Constant	-2.03543***	-5.49	-1.7601***	-13.08
Sigma_ η (Standard Error)	0.90937	(0.029)	0.88327	(0.011)
τ	0.45264		0.43825	
Log likelihood	-6930.14		-47692.11	
Chi-square Joint Significance Test Statistic (P-value):[b]				
Lfcompete1 –Lfcompete15	15.00 (0.451)		1.71(0.624)	
Access1-Access15	31.89 (0.007)		39.20 (0.001)	
Informal1 – Informa115	26.17 (0.036)		86.38 (0.000)	

* (**) [***] Statistically significant at the 10% (5%) [1%] level of significance.
(a) Includes controls for year-quarter effects.
(b) Individual effects are allowed to depend on per period values of variables suffixed by *1* through *15*. To conserve on degrees of freedom, individual effects depend on over time means for other variables, suffixed by *b*.

Table 5: Average Partial Effects - Estimated Probability of TANF Recipient Being Employed Full-time[a,b]				
Variable	**1999:Q2-2002:Q4[c]**	**1999:Q2**	**2001:Q1**	**2002:Q4**
Whites:				
Ftemploylag	0.3298	0.2911	0.3327	0.3215
Children	-0.0098	-0.0103	-0.0096	-0.0085
Informal	0.0302	0.0224	0.0291	0.0298
Lfcompete (One SD)	-0.0217	-0.0150	-0.0229	-0.0215
*Access (*One SD)	0.0022	0.0015	0.0023	0.0021
Nonwhites:				
Ftemploylag	0.3188	0.2816	0.3184	0.3248
Children	-0.0037	-0.0026	-0.0039	-0.0039
Informal	0.0626	0.0488	0.0640	0.0636
*Access (*One SD)	0.0012	0.0008	0.0012	0.0013

[a] Predicted responses to a unit increase in key control variables obtained from the dynamic unobserved effects probit model. SD refers to standard deviation.

[b] For a given dummy variable (state dependence or informal child care), the average partial effect is for a discrete change from 0 to 1.

[c] Computed as a simple average of APEs for 15 periods.

Table 6: Descriptive Statistics for Nonwhite TANF Public Housing Residents (Obs=35041)[a] (1999:Q1 - 2002:Q4 Unbalanced Panel)				
Variable	**Mean**	**Std. Dev.**	**Min**	**Max**
Dependent Variable				
Ftemploy	0.19	0.40	0	1
Individual Characteristics				
Age	33.84	10.42	16	65
Agesquared	1253.89	795.24	257.32	4219.30
Hsgrad	0.32	0.47	0	1
Longterm	0.78	0.42	0	1
Children	2.71	1.60	1	13
Access to Job Growth and Competing Labor Supply				
Lfcompete	7160.43	3094.57	355.70	11183.79
Access	-88.21	673.03	-4805.66	4894.26
Childcare				
Ccemp	6.00	13.03	0.00	119.67
Informal	0.44	0.50	0	1
Neighborhood and Transit Variables				
Povrate	0.55	0.18	0.02	0.77
Transitqm	0.90	0.30	0	1
Counties				
Fulton	0.88	0.32	0	1

[a] There are 2906 TANF recipients observed for a minimum of 2 and a maximum of 16 quarters, with an average of 12.1 quarters per individual.

Table 7: Results for Nonwhite TANF Public Housing Residents (Obs=22590, 1999Q2 – 2002Q4)[a]

	Chamberlain Random Effects Probit		Dynamic Unobserved Effects Probit	
Variable	**Coef**	**t-stat**	**Coef**	**t-stat**
Ftemploylag			1.43367***	38.97
Age	-0.96034*	-1.83	0.03665*	1.68
Agesquared	-0.00271***	-4.89	-0.00081***	-2.67
Hsgrad	0.3766***	4.84	0.13524**	1.99
Longterm	-0.45646***	-5.18	-0.22391***	-2.81
Children	0.01886	0.75	0.0279	0.82
Lfcompete	0.00001	0.28	0.00003	0.87
Access	0.00002	1.39	0.00001	0.46
Ccemp	0.00245	0.91	0.00215	0.56
Informal	0.99077***	15.83	0.51691***	6.52
*Informal*Children*	-0.01647	-0.86	-0.0214	-0.94
Povrate	0.11079	0.33	0.24198	0.37
Transitqm	0.80401*	1.92	-0.17777	-0.1
Fulton	-0.84018**	-2.19	0.03238	0.02
Ageb	0.99159*	1.88		
Agesquaredb	0.00215***	3.31		
Childrenb	-0.03002	-0.63	0.01325	0.23
Lfcompeteb	0.00002	0.46		
Accessb	0.00068	1.18		
Ftemploy0			1.81882***	15.59
Ccempb	0.00278	0.68	-0.00259	-0.55
Informalb	1.01117***	4.00		
*Informal*Childrenb*	0.0542	0.67	-0.03038	-0.39
Transitqmb	-0.92367**	-2.21	0.24616	0.14
Fultonb	0.99724***	2.67	0.01721	0.01
Constant	-5.7063***	-5.05	-3.03701***	-7.61
Sigma_ η (Standard Error)	1.63583	(0.034)	0.86118	(0.032)
τ	0.72796		0.42583	
Log likelihood	-10087.92		-5844.8	
Chi-square Joint Significance Test Statistic (P-value):[b]				
Lfcompete1 –Lfcompete15			10.26 (0.803)	
Access1-Access15			42.30 (0.000)	
Informal1 – Informal15			31.67 (0.007)	

* (**) [***] Statistically significant at the 10% (5%) [1%] level of significance.

(a) Models control for year-quarter effects.

(b) Individual effects are allowed to depend on per period values of variables suffixed by *1* through *15*. To conserve on degrees of freedom, individual effects depend on over time means for other variables, suffixed by b.

Table 8: Average Partial Effects - Estimated Probability of Nonwhite TANF Public Housing Resident Being Employed Full-time[a,b]				
Variable	**1999:Q2-2002:Q4[c]**	**1999:Q2**	**2001:Q1**	**2002:Q4**
Ftemploylag	0.2910	0.2261	0.2833	0.3044
Informal	0.0672	0.0467	0.0688	0.0685
Access (One SD)	0.0009	0.0005	0.0009	0.0010

[a] Predicted responses to a unit increase in key control variables obtained from the dynamic unobserved effect probit model. SD refers to standard deviation.

[b] For a given dummy variable (state dependence or informal child care), the average partial effect is for a discrete change from 0 to 1.

[c] Computed as a simple average of APEs for 15 periods.

Appendix A: Detailed Results from Dynamic Unobserved Effects Probit Model of Table 4

Table A1: Detailed Results from Dynamic Unobserved Effects Probit[a] (1999Q2 – 2002Q4)				
	White (Obs=29055)		**Nonwhite (Obs=168705)**	
Variable	**Coef**	**t-stat**	**Coef**	**t-stat**
Ftemploylag	1.62937***	49.85	1.44756***	114.3
Age	-0.00224	-0.13	-0.00867	-1.24
Agesquared	-0.00013	-0.59	-0.00006	-0.67
Hsgrad	0.15145***	2.6	0.14468***	6.51
Longterm	-0.12732**	-2.09	-0.13327***	-5.5
Children	-0.11142**	-2.44	-0.0227**	-1.96
Lfcompete	-0.00007	-1.61	0.00000	0.09
Access	0.00008	1.16	0.00002	1.42
Ccemp	-0.00248	-1.14	0.00055	0.88
Informal	0.10662	1.39	0.38128***	14.32
*Informal*Children*	0.05905*	1.9	-0.00026	-0.03
Povrate	-0.34231	-0.5	-0.08939	-0.81
Transitqm	0.05753	0.26	-0.05909	-1.05
Pubh	0.04055	0.17	-0.00122	-0.03
Clayton	0.14545	0.47	0.02835	0.34
Dekalb			-0.00129	-0.02
I20South	0.12285	0.38	-0.29687**	-2.31
I20North	0.13085	0.43	-0.11504	-1.03
Ftemploy0	1.76830***	21.96	1.61747***	49.26
Lfcompete1[b]	-0.00007	-1.21	0.00002	1.49
Lfcompete2	0.00008	0.9	0.00000	-0.14
Lfcompete3	-0.00008	-0.76	-0.00002	-1.08
Lfcompete4	0.00007	0.6	-0.00001	-0.3

Lfcompete5	-0.00016	-1.19	0.00001	0.28
Lfcompete6	0.00014	1	-0.00003	-1.14
Lfcompete7	-0.00002	-0.11	0.00004	1.45
Lfcompete8	0.00001	0.08	0.00002	0.68
Lfcompete9	-0.00024	-0.75	-0.00004	-1.2
Lfcompete10	0.00040	1.24	-0.00002	-0.47
Lfcompete11	-0.00015	-0.66	0.00004	1.16
Lfcompete12	0.00006	0.19	-0.00001	-0.24
Lfcompete13	-0.00007	-0.21	-0.00003	-0.92
Lfcompete14	0.00037*	1.93	0.00003	0.81
Lfcompete15	-0.00027*	-1.76	0.00000	0.00
Access1	0.00027*	1.72	0.00010**	2.15
Access2	-0.00008	-0.6	0.00001	0.29
Access3	0.00016	1	-0.00005**	-2.05
Access4	-0.00021	-1.31	0.00002	0.7
Access5	0.00001	0.05	0.00003	1.29
Access6	0.00027*	1.72	0.00002	0.81
Access7	0.00008	0.49	0.00005**	1.99
Access8	0.00001	0.06	0.00002	0.62
Access9	0.00052***	2.74	0.00010***	4.21
Access10	-0.00001	-0.09	0.00005*	1.87
Access11	0.00004	0.29	0.00003	0.98
Access12	0.00014	0.92	0.00003	1.31
Access13	0.00041**	2.49	0.00005*	1.92
Access14	0.00044**	2.52	0.00003	1.22
Access15	0.00044***	2.59	0.00010***	2.59
Informal1	-0.27332	-1.4	-0.38545***	-4.1
Informal2	-0.00518	-0.06	0.01553	0.45
Informal3	0.16763*	1.72	-0.03767	-1
Informal4	-0.16752	-1.48	0.11969***	3
Informal5	0.20176	1.64	0.03394	0.82
Informal6	0.02128	0.16	-0.03527	-0.76
Informal7	0.08213	0.56	0.11148**	2.23
Informal8	-0.03973	-0.25	0.02756	0.56
Informal9	-0.04443	-0.25	0.0199	0.41
Informal10	0.34919*	1.77	0.01726	0.32
Informal11	-0.6134***	-3.13	0.03726	0.64
Informal12	0.64556***	3.06	-0.01296	-0.22
Informal13	-0.20455	-1	0.06011	1.06
Informal14	-0.00538	-0.03	-0.02071	-0.36
Informal15	-0.05306	-0.35	0.12547***	2.82
Childrenb	0.06301	0.88	-0.01339	-0.73
Ccempb	-0.00098	-0.35	-0.00098	-1.05
Povrateb	-0.43864	-0.55	-0.18668	-1.31

*Informal*Childrenb*	0.01810	0.2	0.06168**	2.41
Transitqmb	0.02137	0.08	0.04167	0.58
Pubhb	0.11460	0.4	0.01874	0.32
Claytonb	-0.27045	-0.78	-0.06012	-0.59
Dekalbb			-0.15282**	-2.15
I20Southb	-0.18888	-0.54	0.22011	1.54
I20Northb	-0.18672	-0.57	-0.08298	-0.67
Constant	-2.03543***	-5.49	-1.7601***	-13.08

* (**) [***] Statistically significant at the 10% (5%) [1%] level of significance.

(a) Includes controls for year-quarter effects.

(b) Individual effects are allowed to depend on per period values of all variables suffixed by *1* through *15*. To conserve on degrees of freedom, individual effects depend on over time means for other variables, suffixed by *b*.