A Migration Study of Mother's Work, Welfare Participation, and Child Development

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Abstract

This paper investigates how women's migration and labor supply behaviors respond to changes in Aid to Families with Dependent Children (AFDC) policies and labor market conditions. It also traces out how these responses influence educational inputs and child outcomes. The research approach incorporates a new empirical framework for characterizing the simultaneity and endogeneity of decision making about migration, welfare program participation, and labor supply, recognizing that all of these decisions could impact their children's achievement outcomes. No other paper has linked migration and work decisions to welfare participation and the impacts of welfare policies on children.

Preliminary results show that poor and low-educated single women with children do change their residential locations in response to changes in welfare policies and labor market conditions. The magnitude of this response in the form of migration, however, is modest. In addition, such policy changes often have large and important impacts on particular at-risk groups. For example, increases in a state's welfare benefits can significantly increase the fraction of in-migrants who newly decide to enter welfare. Similarly, the impacts on the children of those women who would move out of a state in the presence of work requirements are large. On average, using New York as an example, their children's achievement test scores would fall by 3.5 percentile points because of their mothers' new relocation decisions.

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1 Introduction

This paper investigates whether women base their migration decisions on welfare benefits, labor market conditions, and quality of school districts simultaneously, how women's migration and labor supply behaviors respond to changes in Aid to Families with Dependent Children (AFDC) policies and labor market conditions, and how these responses affect their children's achievement outcomes.

Understanding how at-risk individuals change their migration and labor supply behaviors in response to reforms in welfare policies can provide crucial information to policy makers as they design assistance programs to achieve certain desired outcomes. With the passage of the Personal Responsibility and Work Opportunity Reconciliation Act (PRWORA) of 1996, state governments have much greater power in reforming their welfare programs. In particular, researchers from different disciplines have investigated whether changes in Aid to Families with Dependent Children (AFDC) policies cause women to adjust their labor supply and residential location decisions. However, the literature on these issues is far from definite. For instance, few studies analyze the interaction between welfare migration and labor supply decisions. In addition, previous studies provide little consensus on the extent to which inter-state benefit differentials induce welfare recipients to move across states to seek more assistance. [1]

Given the fact that the AFDC program was established in a bid to provide financial assistance to children who were deprived of support due to death, incapacity, or absence of parent (Burke, 1997), we have very limited understanding about the impacts of these welfare-induced behavioral changes on children's achievement outcomes. Researchers who study educational production functions show that migration and labor supply decisions have several channels to interact with child development (see Hanushek (2001), and Blau (1992)). For instance, we would expect that welfare-induced migration might improve children's immediate financial well-being. On the other hand, moving could also have negative impacts on children's achievement outcomes because of disruption of regular schooling. It is, however, not clear what is the net impact on these children whose mothers decide to move. A joint decision of changing employment status and relocation further complicates a modeling of the educational production process.

In seeking to answer the research questions posed at the beginning of this section, this

[1] See review articles by Moffitt (1992) and Brueckner (2000).

paper makes an important advance by developing a conceptual model that characterizes the simultaneity and endogeneity of decision making about migration, welfare program participation, and labor supply. Furthermore, the model recognizes that all of these decisions could impact their children's achievement outcomes. I implement this model by assuming that parents choose their residential location in part because of income prospects, such as employment opportunities and welfare benefits, and in part because of the characteristics of the school districts where they choose to live. At the beginning of each period, parents can choose their place of residence from 3141 counties in the United States. They have complete information about tax laws, school quality, housing costs, the wage offer distribution, and welfare rules in each location. However, wage offers and education production function are stochastic, and parents have to make their residential location choice before knowing child outcomes and the exact wage offer they might receive. After making a place of residence decision, which simultaneously sets her child's consumption of school quality as well as other local economic parameters, a mother receives a wage offer. She then decides whether to participate in the AFDC program and how many hours to work, recognizing that the more time spent in the labor market could reduce her time inputs to the education production process. However, she cannot completely determine her child's outcome in the sense that she only knows the distribution of her child's possible outcomes. Semi-parametric maximum likelihood procedures are used to estimate the structure of her preferences and the stochastic child achievement production process. The statistical model relaxes many functional form assumptions imposed by previous researchers who have studied education production functions and residential location decisions.

The simulation-based computations conclude that poor and low-educated single women with children do change their residential locations in response to changes in welfare policies and labor market conditions. The magnitude of this response in the form of migration, however, is modest. In addition, such policy changes often have large and important impacts on particular at-risk groups. For example, increases in a state's welfare benefits can significantly increase the fraction of in-migrants who newly decide to enter welfare. Similarly, the impacts on the children of those women who would move out of a state in the presence of work requirements are large. On average, using New York as an example, their children's achievement test scores would fall by 3.5 percentile points because of their mothers' new relocation decisions.

The remainder of this paper proceeds as follows. In section 2, I briefly review several important papers that investigate related topics. In section 3, I discuss the model specification. In section 4, I describe the data used in my analysis. In section 5, I report and discuss the estimation and main simulation results. I summarize the findings in section 6.

2 Previous studies

Previous studies about the interactions among welfare participation, labor supply, migration, school choices, and child development are grouped into following four categories: welfare reforms and labor supply; welfare and child development; welfare migration; residential decisions and school choices.

2.1 Welfare reforms and labor supply

A number of researchers have found that certain policies that are intended to encourage low-income women to work have considerable effects on single mothers' labor supply decisions. For example, Meyer and Rosenbaum (1999) use CPS data to show that a substantial share of the increase in work by single mothers is induced by the EITC. They also conclude that policies that make work more attractive do increase women's hours of work significantly. Hoynes (1996) models AFDC-UP (Unemployed Parent) participation and couple labor supply, and finds that labor supply and welfare participation among two-parent families are highly responsive to changes in the benefit structure. In particular, these parents would increase their hours of work significantly in the absence of the program.

2.2 Welfare and child development

It is noted that the potential effects of recent welfare reforms on child development are not addressed sufficiently. Most existing studies on welfare receipt have not included young children's cognitive outcomes, even though a substantial literature investigates the impact of welfare receipt on school attainment, intergenerational welfare receipt, and teenage childbearing (see Haveman and Wolfe (1995), and Moffitt (1992)).

Levine and Zimmerman (2000) find that welfare exposure of NLSY children is considerable and further confirm that maternal welfare receipt is negatively correlated with children's outcomes. They also find that the children have lower scores on tests of cognitive development and experience greater behavioral problems as the extent of this exposure increases. However, they cannot find any causality between welfare receipt and low scores after controlling for mothers' characteristics. A study by Smith et al. (2001) explicitly examines patterns of mothers' AFDC receipts and associates them with mothers' emotional distress, parental inputs in child development, and children's cognitive scores. The authors find a strong negative relationship between receiving welfare and child scores at age 3 years. Even controlling for family background characteristics and family income at age 1 year, they cannot explain a child outcome deficit between families that were on AFDC before children's first birthday and families than were never on AFDC. Smith and her co-authors recognize that mothers might be forced to leave AFDC due to changes in policy rules and , in turn, take low-wage jobs. It is less clear how the two groups of women differed in their work decisions.

A study by Yoshikawa (1999) uses longitudinal data from the NLSY to address the gap in the research literature regarding the effects of welfare reform on children. The main issues investigated in his paper include whether welfare dynamics and different childcare services are associated with mothers' earnings and children's outcomes. Welfare dynamics are characterized by the total time on welfare, degree of cycling on and off welfare, and degree of association between work and welfare. Yoshikawa finds no notable associations of the welfare dynamics with cognitive outcomes. However, he notes that the welfare duration has negative effects on cognitive outcomes among a subgroup of children whose mothers work few hours while on welfare. Endogeneity might help interpret this finding, but Yoshikawa's approach is not suitable for addressing this issue.

2.3 Welfare migration

A recent paper by Meyer (1998) addresses explicitly several reasons why studies using different approaches could give rise to different estimates about the magnitude of welfare migration. He emphasizes that not controlling for important migration determinants tends to bias estimates on the magnitude of welfare migration. For instance, Blank (1988) finds significant welfare-induced migration by estimating a model with joint decisions about migration and AFDC participation. One main problem in her analysis is that instead of modeling work choice explicitly she uses hours worked as an independent variable. Given the fact that high-benefit states tend to have high wage rates, one cannot infer if her findings are due to wage earnings or welfare benefits.

Moffitt (1992) and Brueckner (2000) provide two critical reviews about the literature on welfare migration, and several new studies further have attempted to shed light on this topic. Gelbach (2002) estimates models relating welfare benefit generosity to five-year out-of-state migration among single mothers. He finds substantial evidence of welfare migration, with effects diminishing as women's oldest children age from 0 to 11 years old. However, his results on women whose children are between 5 and 11 years old show that welfare-induced migration becomes moderate as children reach school age. Kaestner et al. (2001) find a modest migration effect induced by recent welfare policy changes that have made public assistance less attractive. Furthermore, they associate these moves with employment and argue that welfare reform has motivated people to move for economic reasons such as better employment opportunities, even though the authors admit that their approach is not adequate to identify this joint decision.

2.4 Migration and school choices

Bayer (2000) has attempted to model residential location decision and school choice simultaneously. He highlights the phenomenon that low-income, less educated, and minority households tend to live in relatively poor quality public school districts. Bayer estimates a general equilibrium model of the residential location and schooling decisions of households with elementary school-aged children in California. The model characterizes individuals with different characteristics choosing over a set of location choices, school choices, and housing choices. He concludes that a considerable portion of the difference in the consumption of school quality can be attributed to housing, peer, amenities, and other characteristics. Bayer's model implies that parents derive utility directly from school quality. This approach misses many important relationships, such as the impacts of mother's labor supply decision on child outcomes and interactions between parental and school inputs in the educational production process. Given the fact that poorer school quality is often associated with fewer employment opportunities and lower welfare benefits, these omitted pieces should help identify the role of school quality in a migration model.

Ferreyra (2001) estimates a general equilibrium model of household residential and school choices in an economy with multiple public school districts and private schools. Her simulation results indicate that households migrate towards neighborhoods with lower housing quality while sending their children to private schools. This study does not address how child achievement outcomes are associated with this migration.

3 The model

3.1 Introduction

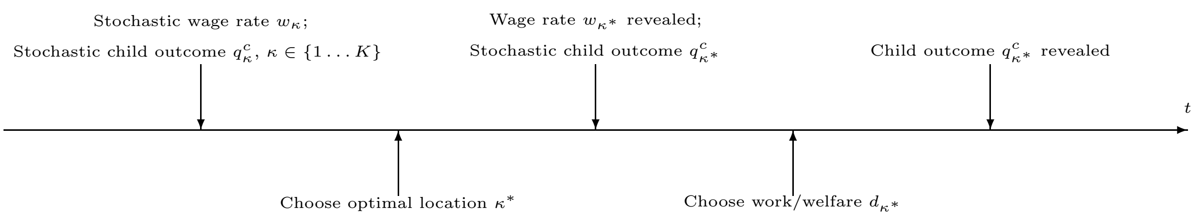
I model migration as part of a stochastic utility optimization problem, in which a mother's hours of work, welfare participation, and place of residence are chosen to maximize her expected utility subject to a budget constraint incorporating tax, housing cost, and transfer programs. The basic assumption is that parents choose their residential location in part because of income prospects, such as employment opportunities and welfare benefits, and in part because of the impact the characteristics of the school district they choose can have on their children. At the beginning of each period, parents can choose their place of residence from 3141 counties in the United States. They have complete information about tax laws, school quality, housing costs, the wage offer distribution, and welfare rules in each location. However, wage offers and education production function are stochastic, and parents have to make their residential location choice before knowing child outcomes and the exact wage offer they might receive.

A mother receives a wage offer after making a place of residence decision, which simultaneously determines her child's consumption of school quality as well as other local economic parameters. She then decides whether to participate in the AFDC program and how many hours to work, recognizing that the more time spent in the labor market could reduce her time inputs to the education production process. However, she cannot completely determine her child's outcome in the sense that she only knows the distribution of her child's possible outcomes and how this distribution varies with her work and welfare decisions.

3.2 The time line

Suppose there are K locations. In the previous period, $t-1$, the location of a family is k_{t-1} and at the end of $t-1$ the mother knows the distribution of wage draws w_κ for each location $\kappa \in \{1, \ldots, K\}$. Wage offer distributions vary across localities. Additionally, in each locality, women with different education levels, ethnicities, and ages also have different wage offer distributions. At the beginning of each new period t and after choosing the location of residence, the mother receives a wage offer and has to make hours of work and welfare participation decisions.

The time line of this model is described as follows



3.3 The utility function

To simplify notations, I drop all subscripts t in this subsection. Let $k = \kappa \in \{1, 2, 3, \ldots, K\}$ represent a specific location. Consider a one-period model, in which a woman i has preferences over goods consumption, $X_{i\kappa}$, the quality of child, $Q_{i\kappa}$, and the mother's hours devoted to non-market activities, $l_{i\kappa}$.[2] Let those preferences be represented by a direct utility function as follows

$$U_i = U_i(X_{i\kappa}, Q_{i\kappa}, l_{i\kappa}, v_{i\kappa}, a_{i\kappa}).$$

The net consumption is expressed as

$$X_{i\kappa} = w_{i\kappa} h_{i\kappa} + y_i - x^o_\kappa - \tau_{i\kappa} + a_{i\kappa} B_{i\kappa}, \tag{1}$$

where $w_{i\kappa}$ represents a wage draw at location κ, which is unknown to the mother prior to the migration decision being made. However, she does know the distribution of wage draws in each location κ. $h_{i\kappa}$ represents mother's hours spent on working in the labor market during a given year. The empirical model discretizes hours of work (in thousands) into no work ($h = 0$), work part-time ($h = 1$), and work full-time ($h = 2$). A woman is defined as a full-time worker if she works more than 30 hours per week for more than 45 weeks in a year. If she works and is not a full-time worker, she is defined as a part-time worker. y_i denotes non-labor income, which includes household non-labor income and earnings of others in the household i aside from the mother. x^o_κ explicitly measures the average housing cost in location κ. $\tau_{i\kappa}$ is the sum of federal and state tax liabilities for individual i, given her marital status, number of dependents, wage income and non-labor income. $a_{i\kappa}$ is a binary indicator of AFDC receipt. If individual i participates in AFDC ($a_{i\kappa}$=1) she could receive AFDC

[2] I only model women who have children. In addition, the unit of observation is a mother-child pair.

benefit $B_{i\kappa}$, which is a function of her income, family size, and AFDC rules in location κ. Detailed information about the calculation of tax liabilities and AFDC benefits is provided in Appendix B and C respectively.

For simplicity, I assume that her work choice ($h_{i\kappa}$) is made in conjunction with welfare participation ($a_{i\kappa}$). This joint decision, $d_{i\kappa}$, then is restricted to the following set:

$$d_{ik} = \begin{cases} 1 & : \text{not working } (h_{i\kappa} = 0) \text{ and not on AFDC } (a_{i\kappa}{=}0) \\ 2 & : \text{not working } (h_{i\kappa} = 0) \text{ and on AFDC } (a_{i\kappa}{=}1) \\ 3 & : \text{working part-time } (h_{i\kappa} = 1) \text{ and not on AFDC } (a_{i\kappa}{=}0) \\ 4 & : \text{working part-time } (h_{i\kappa} = 1) \text{ and on AFDC } (a_{i\kappa}{=}1) \\ 5 & : \text{working full-time } (h_{i\kappa} = 2) \text{ and not on AFDC } (a_{i\kappa}{=}0). \end{cases}$$

However, in each period women might have to choose from a subset of the above five choices, depending on her circumstances. I further impose that married women do not have the option of receiving AFDC. In practice, married couples were eligible to receive cash assistance under the AFDC-Unemployed Parent (AFDC-UP) program. However, the AFDC-UP program adopted stricter eligibility requirements and, in turn, had smaller enrollments. In the full sample of 12387 person years, only 363 married women, whose spouses were present, received AFDC benefits. The paper focuses on the basic AFDC program and the participation in AFDC-UP is not modeled. In addition, I do not allow women who worked full-time to receive welfare benefits because in the data very few women who worked full-time received AFDC benefits. The eligibility rule of AFDC is further described in Appendix B.

The labor supply of fathers is assumed to be predetermined and exogenous. The static framework used in this preliminary paper also implicitly treats the parents' prior family formation, marital status, fertility, and education as exogenous variables. For simplicity I ignore capital markets by assuming that parents do not save or borrow.

$Q_{i\kappa}$ is measured by her child's Peabody Individual Achievement Test (PIAT) score, $q^c_{i\kappa}$, relative to her own Armed Forces Qualification Test (AFQT) score, q^m_i, implying that high achieving mothers have different standards in evaluating child success than lower achieving mothers.[3] Explicitly, it is given by

$$Q_i = f_Q(q^c_{i\kappa}, q^m_i) = q^c_{i\kappa}/q^m_i. \tag{2}$$

[3] This specification is based on a preliminary investigation in which I examined whether the child's score relative to a power of the mother's score mattered. In these estimations the power is always significantly different from zero and I could never reject the hypothesis that the power was equal to one, implying that the relative score is appropriate.

The PIAT is among the most widely used academic achievement assessment instruments that have demonstrably high re-test reliability and concurrent validity (Markwardt, 1989).[4] The AFQT is an IQ test adapted for the military and its goal is to ascertain test takers' general cognitive abilities.[5]

Leisure time, $l_{i\kappa}$, is defined to include maternal time directly devoted to child education, other household production activities, and leisure.[6] Explicitly, it satisfies

$$T = h_{i\kappa} + l_{i\kappa}, \tag{3}$$

where T is the total time available to the mother.

$v_{i\kappa}$ is a binary indicator of migration, which occurs when κ is different from the location choice in period $t-1$.

In addition to affecting the consumption component, $X_{i\kappa}$, the AFDC participation indicator, $a_{i\kappa}$, also directly enters the utility function.

3.4 The empirical specification

Empirically, the utility function is specified with relevant arguments in power functions as follows

$$\begin{aligned} & U_{ik}(X_{ik}, Q_{ik}, l_{ik}, v_{ik}, a_{ik} | \mu_i, \varepsilon_{id}, \epsilon_{ik}) \\ = \quad & \frac{(X_{ik} + X_{0i})^{\gamma_1}}{\gamma_1} + \frac{\alpha_2 (Q_{ik} + Q_0)^{\gamma_2}}{\gamma_2} \\ & + \sum_{\delta=1}^{5} [1(d_{ik} = \delta) \cdot (\alpha_{3i\delta} + \varepsilon_{i\delta})] + a_{ik} s \\ & + v_{ik} \lambda_{ik} + \epsilon_{ik}. \end{aligned} \tag{4}$$

$1(\cdot)$ is an index function. The consumption component has a minimum requirement, X_{0i}. The child quality component also has a minimum part, Q_0, which is a constant. I

[4] The PIAT is individually administered during household interviews. A body of literature has studied limitations in the use of standardized tests as measures of educational outputs (see Koretz (2003)). The PIAT is less likely to be subject to some problems encountered by standardized achievement tests, such as cheating, coaching, and reallocating achievement.

[5] A mother's AFQT score also directly enters educational production function.

[6] This definition does not imply that if a mother increases her hours of work her time input to child development must decrease by the same amount. However, it is quite likely that a full-time working mother has less time available for her child's educational production than does a part-time work mother.

allow hours of work decisions to influence utility discretely through part-time and full-time work utility costs α_{3id}, $d = \delta \in \{1, \ldots, 5\}$. ε_{id} is maternal evaluation of the attributes of the work/welfare status, d. In addition, ε_{id} is assumed to be independently and identically distributed over different hours of work and welfare choices and to follow an Extreme Value distribution. s is a disutility component associated with welfare participation, accounting for nonparticipation among eligible women. Following Moffitt (1983), this "stigma" term is separable. I specify three specific moving costs (λ_{ik}) that directly affect a woman's utility.[7] The first is for moves within the state where she lived during the preceding interview year, and the second is for moves outside of this state but within its geographic region, and the third is for moves outside the geographic region. I estimate the magnitude of all of these costs. Maternal evaluation of the attributes of location $k = \kappa \in \{1, 2, 3, \ldots, K\}$ is ϵ_{ik}, which is assumed to be independently and identically distributed over different locations and to follow an Extreme Value distribution.

Additional sources of heterogeneity are introduced into (4). First, I specify the parameters measuring the disutility from work/welfare choice, α_{3id}, as functions of the number of children between the ages of 0 and 5 (n_y), the number of children between the ages of 6 and 17 (n_o), as well as a time-invariant child-specific heterogeneity component μ_i:

$$\alpha_{3i\delta} = \begin{cases} 0 & \text{if } \delta = 1, 2 \\ f_{\alpha_{pt}}(\mu_i, n_{yi}, n_{oi}) & \text{if } \delta = 3, 4 \\ f_{\alpha_{pt}}(\mu_i, n_{yi}, n_{oi}) + f_{\alpha_{ft}}(\mu_i, n_{yi}, n_{oi}) & \text{if } \delta = 5, \end{cases}$$

where μ_i represents the unobserved children's heritable endowment at the age when they enter the data set (age 5 or age 6). Second, the "reserve" consumption, X_{0i}, is defined as a function of individual heterogeneity $\mu_i : X_{0i} = f_{X_0}(\mu_i)$.

Empirically, the child quality production function q^c_{ik} is discretized, and estimated with a "hazard" model as described below (Gilleskie and Mroz, 2002).[8] This hazard model assumes that at each point in the range of discretized child outcomes, the child has a particular probability of advancing to a higher level, conditional upon reaching the current level. The hazard specification does not impose arbitrary assumptions about error distributions. Gilleskie and Mroz (2002) have demonstrated that this estimation strategy provides accurate and precise

[7] Given that moving costs are unobserved, to avoid identification problems, instead of modeling both psychic and monetary moving costs, I only incorporate the latter.

[8] The standard deviation of child test scores within the sample used for this study declines from 0.288 to 0.285 after the percentile scores are discretized into deciles. In other words, the loss of variation due to discretization is only 1.2%.

estimates of derivatives of expected outcomes for a wide range of types of explanatory variables. In this study, the hazard estimation method also alleviates the computational cost involved in error integrations. The hazard function in this model is defined by a logit function of the sum of a level-varying baseline hazard and a set of covariates. The probability of an advance to a higher level, conditional on reaching the current level, p, is given by

$$\Pr(q^c_{i\kappa} > p | q^c_{i\kappa} \geq p) = \frac{\exp\left[f_{cv_q i} + f_{bl_q(p)}\right]}{1 + \exp\left[f_{cv_q i} + f_{bl_q(p)}\right]}, \tag{5}$$

where q^c_{ik} is the observed score of child i in location $k = \kappa$, and the component $f_{cv_q i}$ is given by

$$f_{cv_q i} = f_q(E_i, H_i, S_{i\kappa}, \mu_i), \tag{6}$$

where E_i, H_i, and $S_{i\kappa}$ are vectors of child's characteristics, mother's characteristics, grade-specific school characteristics respectively. Detailed description of these variables is given in Section 4. Empirically, the baseline hazard at score p is specified as follows.

$$f_{bl_q(p)} = \sum_{n=1}^{3} \{\theta_{qn}[-\log(P - p)]^n\}, \tag{7}$$

where n is the order of polynomials, and P is the highest score level. I have also relaxed several of the separability assumptions in this framework to allow for interactions of baseline hazard, age of the child, and school and parent characteristics by interacting elements of $f_{cv_q i}$ and $f_{bl_q}(p)$.

Hourly wage rates are discretized into G groups, and the probability of having a wage offer better than g conditional on being not worse than g is estimated in the similar fashion as child outcomes.

$$\Pr(w_{i\kappa} > g | w_{i\kappa} \geq g) = \frac{\exp(f_{cv_w i} + f_{bl_w(g)})}{1 + \exp(f_{cv_w i} + f_{bl_w(g)})}, \tag{8}$$

where

$$f_{cv_w i} = f_w(\overline{W_{i\kappa}}, H_i, \mu_i), \tag{9}$$

and

$$f_{bl_w(g)} = \sum_{n=1}^{3} \{\theta_{wn}[-\log(G - g)]^n\}. \tag{10}$$

$\overline{W_{i\kappa}}$ is the mean wage rate for women with the same education level, ethnicity, and age in each locality, so this formulation allows for a different wage distribution in each locality.

Furthermore, the heterogeneity type of individual i, μ_i, is assumed to be constant over time for individual i. Her unobserved tastes for goods consumption and leisure, and unobserved determinants in wage offers and production functions are assumed to be functions of this heterogeneity term, which is arbitrarily distributed among the whole population. The specification for the unobserved elements in preferences, production functions, and wage offer equations allows unrestricted correlations among them and helps control for unobserved endogenous determinants in these components. I also use equally spread points on the unit interval for the heterogeneity term, μ_i, and estimate the probability of each value of μ_i.

3.5 Value functions and estimation

As described earlier, place of residence and work/welfare decisions are made sequentially with a household first making a location decision, followed by the realization of a wage offer and the mother's subsequent work/welfare decision, after which the child's achievement score is realized. When making her work/welfare choice, the mother takes into account the effect of her work/welfare decision as well as of the location-specific school quality level on the expected child outcome. Similarly, when the place of residence decision is being made, the effect of this decision on subsequent work/welfare decisions and the effect of both on the expected child outcome are taken into account. The solution to this stochastic optimization problem can be obtained by solving backwards: first, making the optimal work decision for each possible location choice and wage offer; second, making the optimal location choice. To simplify notations, the subscripts i and t are dropped.

If the mother ends up in location $k = \kappa$, she receives wage draw w_κ and learns the utility shocks associated with each work/welfare decision, *i.e.* $\varepsilon_d = (\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_5)$. After learning the above information, she makes a joint decision about hours of work and welfare participation. Given location choice κ and wage rate offer w_κ the optimal work/welfare decision can be defined as

$$\delta^*_\kappa = \underset{d_\kappa}{argmax}\{u_\kappa(\Omega, \mu | w_\kappa, d_\kappa) + \varepsilon_d\}, \tag{11}$$

where Ω is an information set, $\Omega = \{E, H, S\}$. E, H, and S are vectors of child's characteristics, mother's characteristics, grade-specific school characteristics in all locations respectively.

This is an expected maximization problem because the child's educational outcome is stochastic (though influenced by work/welfare choices). For each work/welfare choice, the expected utility, after integrating over all possible test score outcomes, is given by

$$u_\kappa(\Omega,\mu|w_\kappa,d_\kappa)=\sum_{p=1}^{P}\left\{\Pr\left(q_\kappa^c=p\ |\Omega,\mu,w_\kappa,d_\kappa\right)\overline{U}_\kappa(X_\kappa,Q_\kappa,l_\kappa,v_\kappa,a_\kappa|\Omega,\mu,w_\kappa,d_\kappa)\right\}, \qquad (12)$$

where $\overline{U}_\kappa(\cdot)$ is the deterministic part of equation (4) conditional on location choice κ and work/welfare decision d_κ.

When the location decision is being made, the woman does not know the actual wage offer at each location, nor does she know the realizations of the utility shocks associated with her future work/welfare decisions. For any given wage offer in location κ, with ε_d being *i.i.d.* Extreme Value errors, the value function conditional on location choice κ and wage offer w_κ is given by

$$\begin{aligned} V(\Omega,\mu|\kappa,w_\kappa,\epsilon_\kappa) &= \underset{d_\kappa}{EMAX}[u_\kappa(\Omega,\mu|w_\kappa,d_\kappa)+\varepsilon_d+\epsilon_\kappa] \\ &= b_1\log\left\{\sum_{d_\kappa=1}^{5}\left[\exp\left(\frac{u_\kappa(\Omega,\mu|w_\kappa,d_\kappa)}{b_1}\right)\right]\right\}+\epsilon_\kappa, \end{aligned} \qquad (13)$$

where b_1 is a parameter defining the variance of the Extreme Value distribution and the equality follows from the additive separability of the utility function in both errors, combined with the assumed independence (conditional on μ) of ε_d and ϵ_κ.

The probability of making work/welfare choice δ conditional on a wage draw w_κ to the researcher is given by

$$\Pr(d_\kappa=\delta^*|\Omega,\mu,\kappa,w_\kappa)=\frac{\exp\left[\frac{u_\kappa(\Omega,\mu|w_\kappa,\delta^*)}{b_1}\right]}{\sum\limits_{\delta'=1}^{5}\exp\left[\frac{u_\kappa(\Omega,\mu|w_\kappa,\delta')}{b_1}\right]}. \qquad (14)$$

When making a residential decision, the wage offer in each possible destination κ is unknown. Integrating the expected utilities defined in equation (13) over all possible wage offers in location κ yields

$$\begin{aligned} V(\Omega,\mu|\kappa,\epsilon_\kappa) &= \sum_{g=1}^{G}\left[\Pr(w_\kappa=g|\Omega,\mu)\cdot V(\Omega,\mu|\kappa,w_\kappa=g,\epsilon_\kappa)\right] \\ &= \widetilde{V}(\Omega,\mu|k)+\epsilon_\kappa. \end{aligned} \qquad (15)$$

At this time, we assume the agent knows ϵ_k for all locations (but not the utility shocks, ε_d, which are associated with work/welfare decisions within locations), so she chooses

$$\kappa^* = \underset{k}{argmax}\{\widetilde{V}(\Omega, \mu|k) + \epsilon_k\}. \tag{16}$$

Assuming *i.i.d.* Extreme Value distributed ϵ_k, the probability of the mother choosing location κ^* to the researcher is given by

$$\Pr(k = \kappa^*|\Omega, \mu) = \frac{\exp\left[\frac{\widetilde{V}(\Omega,\mu|\kappa^*)}{b_2}\right]}{\sum_{\kappa'=1}^{K} \exp\left[\frac{\widetilde{V}(\Omega,\mu|\kappa')}{b_2}\right]}. \tag{17}$$

Unfortunately, direct estimation of (17) is computationally costly because the choice set for locations is very large. In particular, this location choice set consists of 3141 counties in the United States. However, it is still possible to estimate the model consistently. The IIA property implies that the conditional probabilities of choosing from a subset of the full choice set equal the choice probabilities when the choice set equals the subset. McFadden (1978) shows that the set of all choices, or alternatives, can be replaced with a probability sample of the alternatives.[9]

As a practical matter the size of the subset among the complete choice set has yet to be determined. A series of Monte-Carlo simulations show that a subset of 10 choices would be sufficient. The size of random choice subset is set to 15 in this paper.[10]

Hence, equation (17) is re-written as follows

$$\Pr(k = \kappa^*|\Omega, \mu) = \frac{\exp\left[\frac{\widetilde{V}(\Omega,\mu|\kappa^*)}{b_2}\right]}{\sum_{\kappa' \in D(\kappa^*)} \exp\left[\frac{\widetilde{V}(\Omega,\mu|\kappa')}{b_2}\right]},$$

where $D(\kappa^*)$ is a random sample of 15 elements from the full location choice set $\{1, 2, \ldots, 3141\}$, always including the actual choice κ^*. The derivation of the modified equation (18) is described in Appendix D.

[9] The chosen alternative is always included. In addition, it is necessary to include weighting terms unless the sampling method is simple random sampling. Also see Arcidiacono (2002) for another application of McFadden's theorem.

[10] I have used the Monte-Carlo method to test the sensitivity of estimates to the sampling size. Given a multinomial logit model with 3000 choices and 6000 observations, which is comparable to the model in the paper, I find that coefficient estimates and the standard errors are nearly identical to each other after choice sample size is greater than 10. This finding is also insensitive to the value of the pseudo R-square.

3.6 The estimation procedure

After deciding to reside in location κ^* at the beginning of time period t, the wage draw, $w_{\kappa^* t}$ at location κ^* is observed by the researcher only when the woman is working ($h \neq 0$). For non-workers ($h = 0$), it is necessary to integrate over all possible wage offers. Assuming that heterogeneity factor μ has a discrete distribution taking on J different values, with corresponding probabilities $\Pr(\mu_j)$, $j = 1, \ldots, J$, the likelihood function for individual i is given by

$$
\begin{aligned}
L_i = \sum_{j=1}^{J} \Bigg\{ \Pr(\mu_j) \prod_{t=t_0}^{T_i} \Bigg\{ & \Pr(k_{it} = \kappa^* | \Omega_{it}, \mu_j) \\
& \left\{ \Pr(w_{i\kappa^* t} = w^*_{i\kappa^* t} | \Omega_{it}, \mu_j) \Pr(d^*_{i\kappa^* t} | \Omega_{it}, \mu_j, \kappa^*, w^*_{i\kappa^* t}) \right\}^{1(h_{i\kappa^* t} \neq 0)} \\
& \left\{ \sum_{g=1}^{G} [\Pr(w_{i\kappa^* t} = g | \Omega_{it}, \mu_j) \Pr(d^*_{i\kappa^* t} | \Omega_{it}, \mu_j, \kappa^*, w_{i\kappa^* t})] \right\}^{1(h_{i\kappa^* t} = 0)} \\
& \Pr(q^c_{i\kappa^* t} | \Omega_{it}, \mu_j, \kappa^*, d^*_{i\kappa^* t}) \Bigg\} \Bigg\}.
\end{aligned}
\tag{19}
$$

The sample likelihood function then is given by

$$
L = \prod_{i=1}^{N} L_i. \tag{20}
$$

4 Data Description

Table 1 contains summary statistics for the data used in this analysis. These data come from several sources. The primary data source is the Geocode version of the NLSY79 data set and its Child-Mother Supplement. The Child-Mother Supplement collects detailed information about the young women's children every other year starting in 1986. The unit of observation is a child observed between ages 5 and 15 in 1986 or later, with up to six possible time-period specific observations per child between 1986 and 1998. Because of the structure of the data set, I model some child outcomes at ages 6, 8, 10, 12 and 14, and other children's outcomes at ages 5, 7, 9, 11, 13, and 15. The primary child outcome of interest is the child's percentile score on a mathematics aptitude test, PIAT Mathematics assessment.[11]

[11] In the NLSY79 Child-Mother Supplement, PIAT assessments are administered to all age-eligible children, who are 5 years and older. In particular, the PIAT Mathematics assessment is one of the most reliable child

For the estimation of the production function, I group the percentile scores of the children's math tests into 10 discrete cells (5:1-10, 15:11-20, ... , 95:91-100), and model the determinants of how a child progresses from one cell to the next highest cell through the logit hazard model described in Section 3. The child's score depends upon characteristics of the child such as its age and gender, as well as characteristics of the mother such as her age, marital status, schooling level, part-time and full-time work status, AFQT score, and the family's income after deducting tax liabilities and a measure of the local cost of housing. This production function also depends upon characteristics of the school district where the family resides, such as the dropout rate for 11th graders, average teacher salary as a fraction of the average annual earnings of college educated persons age 27 to 40, per child school district expenditures as a fraction of the average earnings of individuals in the school districts, the teacher/student ratio, and the fraction of white students among all students. These school variables are county means across all schools in the National Center of Education Statistics (NCES): Common Core Data (CCD). In particular, I calculate the means for all these characteristics for each grade between K-12 using CCD. The grade-specific school information is used for each child in the NLSY sample. For instance, a 14-year old child will be matched with school characteristics at the 9th grade.

Table 2 provides economic and demographic characteristics of the sample by employment and welfare status. It shows considerable differences between recipients and non-recipients. Women receiving AFDC benefits tended to be younger, less likely to work, and less educated. For instance, among AFDC-eligible women, 62.4% of the welfare recipients did not work while only 11.9% of the women who were not on AFDC left the labor market. However, this should not be interpreted as the disincentive effect of AFDC because women were likely to be self-selected in the welfare receipt group.

To describe the wage offers available to the individual women in each locality, I model the probability that each woman has an offered wage from each of the five discretized wage rates. As in the child production function model, I use the hazard model to describe transitions across categories. For arguments to these hazard models, I allow for detailed interactions between individual level covariates and local area wages. In particular, for each of three levels of education (less than high school, high school, more than high school), I compute the median wage by single year of age for each of two race categories (white, non-white). For

assessment instruments used in the Child-Mother supplement.

each woman, I assign to her in each locality the median wage corresponding to her education level, race, and age. I use these median wages as explanatory variables for the hazard model of the wage offer distribution. I also allow for separate education level and ethnicity effects, effects of the mother's AFQT score, and effects of the heterogeneity type on the probabilities of each of these discrete wage offers. Estimates for the wage equations are presented in Table 3c.

5 Estimation Results and Discussion

I. Point Estimates of Utility and Production Function Parameters.

Tables 3a, 3b, 3c, 3d, and 3e contain parameter estimates for the production function, utility function, wage offer function, and heterogeneity distribution parameters. The estimates in these tables assume that there is unobserved heterogeneity that can influence the production function, the reserve consumption in the utility function, the utility costs of full- and part-time work, and the wage offer distribution. Four points of support are specified for the distribution of the unobserved heterogeneity. The empirical specifications also permit up to a third order polynomial in the value of the heterogeneity to influence all of the model components, so this is an unrestricted specification of the unobservable heterogeneity in this semi-parametric model. This heterogeneity is modeled as constant throughout the child's years of observation.

Given the complex interactions among most of the covariates in the economic model, it is quite difficult to give a simple interpretation to each of the point estimates. For instance, the interpretation of the parameter estimate of the impact of a mother holding a high school degree on the production function presented in Table 3a is not as straightforward as expected. The economic meaning of this parameter is how a woman being a high school graduate instead of a dropout influences their children's propensity to move to a higher math score category holding everything else constant. The specification of the production function allows most independent variables to interact with the score level and the child age, so the complete effect of those covariates on her child's educational production process can be much more complicated than this. To make an inspection of these impacts possible, I simulate outcomes using the estimated parameters. Three sets of estimates of marginal effects of characteristics on the child's PIAT Math test score, ceteris paribus, are reported in Table 3f. The first column contains OLS estimates. Columns 2 and 3 contain estimates based upon the hazard model for the child scores with controls for unobserved heterogeneity. I simulate how expected test scores would change in response to varying explanatory variables one at a time, normalized to a unit change in the characteristics as is the case with the OLS estimates. The estimates used for the simulation results in Column 2 only incorporate the functional form used for the production function in this analysis. While they do not incorporate any controls for selection or endogeneity, they use exactly the same form of the heterogeneity distribution as I use in the structural model. The estimates used to define the marginal effects in Column 3 were estimated as part of the structural model that incorporates the endogeneity of the location decisions and the endogeneity of the mothers' hours of work decisions. The standard errors of the marginal effects are calculated using a parametric bootstrap (50 replications) simulated using the estimated covariance matrix of the parameter estimators. The preliminary results on the production function in this study, which incorporates a broader choice set for the mother both economically and geographically, are quite consistent with findings from another essay in my dissertation that has been mainly focused on estimating the production function. It is noteworthy that without endogeneity controls, a mother's working part-time and working full-time appear to increase her child's percentile score by 2.8 and 1.1 respectively. After controlling for endogeneity the estimated impacts imply that a mother's working part-time and working full-time, as opposed to not working, reduce the expected percentile score by 0.4 point and 1.7 points respectively.

II. Simulations within the Sample and Preliminary Tests of Goodness of Fit

With parameter estimates from Tables 3a-d, I am able to simulate the migration, work, child development, and welfare participation outcomes within the sample. Table 4a compares the observed outcomes with the simulated behaviors using the model estimates and observed exogenous variables within the sample. In general, the model predicts the means of these important outcomes quite well. Furthermore, several simulation exercises are carried out to inspect the responsiveness of individuals within the sample to four policy changes.

The baseline row in Table 4b shows the simulated outcomes using the actual policy parameters from the data, such as tax laws, AFDC rules, wage distributions, and school characteristics. In this baseline simulation, 11.0% and 76.1% of the women received AFDC benefits and worked respectively. 59.4% of working women worked full-time. In the second row of Table 4b, simulation results are presented for increasing AFDC benefits in each locality. In this case, the proportion of women who participated in AFDC increased by 0.8

percentage point while labor force participation among women fell by only 0.3% percentage point. Given the fact that the fraction of AFDC-eligible women in the full sample was small and a considerable portion of these eligible women were already recipients, the change in AFDC caseloads was small relative to the whole population. These changes in welfare participation and labor supply, however, were considerable relative to the size of AFDC-eligible non-recipients. The mean score of their children did not appear to have changed as a result of increasing benefits. This appears to be due to the fact that there were offsetting changes in residential location choices and labor supply decisions. The rest of the contents in this table show results after imposing strict work requirements, increasing wage rates, and introducing a program similar to EITC across all locations respectively. In particular, requiring all AFDC participants to work dramatically reduced the AFDC enrollment rate by 3.5 percentage points. A significant increase in labor force participation, 3.2 percentage points, also occurred as an outcome of this policy change. Most of these changes appear to be due to women shifting AFDC to full-time employment. Increasing wage rates by 20% in each location reduced the AFDC enrollment rate by 0.4 percentage point and increased the percentage of workers by 1.0 percentage point. As wage rates increase, a fraction of welfare women shifted from AFDC to full-time employment and many non-recipients also shifted from not working to full-time employment.

One of many important benefits from estimating a structural model is that a researcher can identify the impacts of a specific economic factor after perfectly controlling for others. To take advantage of this feature, I carry out a series of experiments after simulating a representative sample as follows.

III. Simulations of Policy Changes on a Representative Sample

As discussed in Section 1, we can use the model developed in this study to predict how women's migration, work, and welfare behaviors respond to changes in welfare policies and labor market conditions. The joint estimation of educational production, in addition, permits the analysis of child development outcomes associated with these changes.

Baseline simulations

Step 1: I generate a national sample of women who were 33-year-old high school dropouts in 1988 (period 0). Each woman had an AFQT score of 0.4, one female child, and no non-labor income. In addition, the number of observations in each county of this sample is in proportion to the county's share of the U.S. population, and the number of observations in the state of New York is normalized to 10,000.

Step 2: I draw a heterogeneity type for each woman in this representative sample and the probability of each type is given by the estimates presented in Table 3e.

Step 3: Following the time-line described in Section 3, each woman received an *i.i.d.* Extreme Value error draw in 1990 (period 1), so that she can compare her expected utility among alternative locations and make a location choice. After choosing place of residence, this representative woman received a wage offer in the chosen location, whose distribution estimates are presented in Table 3c. Along with the wage offer, her preference shocks associated with each of all five work/welfare choices were also revealed. She then made a work/welfare decision to maximize her expected utility in the chosen location. Recall that her child's achievement outcome was still stochastic at this step. After the work/welfare decision had been made, the child outcome was realized by drawing a score from an idiosyncratic distribution estimated within the full model.

After this step, I further focus on two sub-groups. One is called the "New York sample," which consists of 9306 women who stayed in New York in both periods 0 and 1. The other sub-group is called the "New York AFDC sample," which is selected from the New York sample and contains 2680 women who originated from New York in period 0 and stayed in New York as welfare recipients in period 1.

Step 4: For the rest of the time periods, all policy parameters in each location were fixed at their corresponding values in 1990, including tax regulations, welfare rules, and school characteristics. Using the simulated location choices in 1990 (period 1) as given, I repeat Step 3 and Step 4 for two more periods, 1992 (period 2) and 1994 (period 3), recursively.

The simulated out-migration rates, AFDC participation rates, and labor market participation rates in period 3 for the New York sample and the New York AFDC sample are presented in baseline rows in Tables 5a-c and Tables 6a-c respectively. Baseline sections in Appendix Table 2 and Appendix Table 3 also provide children's mean scores for the New York sample and the New York AFDC sample respectively.

The baseline simulation in the New York sample shows that in period 3 about 84.61% of 9306 women still stayed in New York, 4.56% of them left for neighboring Massachusetts, and the rest (10.83%) moved to the other states in the U.S. The baseline row in Appendix Table 2 further presents the detailed information about women who chose different residential locations in period 3. For instance, about 21.45% of the whole New York sample stayed in

New York and received AFDC benefits in period 3; these women constituted 25.4% of the women who stayed in New York through period 3. In addition, 71.71% of the sample stayed and worked in New York in period 3; these women made up 84.8% of all women who stayed in New York in period 3. The mean score of children, whose mothers stayed in New York in period 3, was 0.459 with a standard deviation of 0.259. Women who stayed in New York were more likely to participate in welfare and less likely to work than women who left New York. Given the fact that New York has been one of high-benefit states, out-migrants in New York were more likely to leave the state for reasons other than higher welfare benefits. It appears that many women anticipated better wage offer distributions and better school districts. Consequently, women who left New York had a greater tendency to work and their children had better achievement outcomes than women who stayed.

The baseline simulation results for the New York AFDC sample can be found in the baseline rows in Tables 6a-c and the first section in Appendix Table 3. Conceptually, the main differences between the New York sample and the New York AFDC sample are that women in the latter tended to have tastes in favor of welfare benefits while women in the New York sample represented a more general group of women. Women in the New York AFDC sample were more likely to be at risk of AFDC receipt. For instance, 36.64% of women in the AFDC sample were on AFDC while only 25.06% of the full New York received benefits. In addition, women in the AFDC sample also had a slightly greater tendency to move out of their original place of residence. It is also noteworthy that women in the AFDC sample were less likely to work. This fact might be associated with their children's higher mean scores than those of the children in the New York sample, because holding everything else constant the less time spent in the labor market will increase the direct time inputs in education production.

In the following scenarios I use the same steps described in the baseline simulations to generate the New York sample and the New York AFDC sample in period 1. However, starting from period 2, I change the values of one policy parameter of interest in either New York or Massachusetts so that I can study the impacts of this specific policy change, holding everything else constant. The standard errors of induced out-migration rates are obtained by bootstrapping over 30 draws from the estimated distribution of the parameter vector.[12]

A. Simulations of Changes in AFDC Maximum Benefits

[12] These parameters are drawn from a multivariate normal distribution with a mean vector and a covariance matrix obtained from maximum likelihood estimation.

In one experiment under this category, I reduce the maximum AFDC benefits in New York by 30%. The corresponding outcomes on the New York sample and the New York AFDC sample are presented in Tables 5a-c and Tables 6a-c respectively. In this case, the out-migration rate in the New York sample increased from 15.39% to 15.52%, indicating a out-migration of only 0.13 percentage point, with a standard error of 0.12. Nevertheless, the impact of this policy change on women who stayed in New York was substantial, considering that only 22.6% of them received AFDC benefits and more than 72.6% were working. In the AFDC sample, I find the similar pattern except that women in this sample were slightly more likely to move out when the benefits in New York were reduced. Intuitively, as discussed above, women in the AFDC sample were more likely to move for better welfare benefits.

In the other experiment, AFDC benefit levels were increased by 30% in Massachusetts and the induced out-migration was even smaller. In the New York sample, the induced out-migration was 0.04 percentage point with a standard error of 0.04 while in the AFDC sample the induced change was 0.07 percentage point with a standard error of 0.03. Nevertheless, a quite noteworthy outcome is demonstrated in this scenario. From Massachusetts's viewpoint, even though increasing AFDC benefits hardly induced new in-migrants crossing its state border, the New York residents who would have come to Massachusetts even in the absence of rising benefits still came but with significant changes in their work and welfare behaviors. Specifically, only 1.07% of New York residents moved into Massachusetts and received benefits in the absence of benefit increase. In the presence of the benefit increase, more than 1.23% of New York residents migrated to Massachusetts and received benefits. This represented a 15% increase in the welfare participation rate among in-migrants from Massachusetts's perspective. Intuitively, their recipiency was merely an incidental outcome associated with migration, rather than a motivating factor. These in-migrants who newly took AFDC benefits came to Massachusetts for reasons other than better benefits and they chose welfare after moving if doing so maximized their expected utility, perhaps after receiving poor wage offers.

B. Simulations of Changes in AFDC Work Requirements

The hypothetical policy change in this group of experiments is to impose a work requirement for all AFDC recipients in either New York or Massachusetts. In other words, an individual has to work part-time in order to be eligible for AFDC benefits. Imposing work requirements in New York had larger impacts on women's migration, welfare, and labor supply behaviors than other policy changes reported in this section. Specifically, the induced out-migration was 0.43 and 0.89 percentage points in the New York sample and the AFDC sample respectively. This induced out-migration, however, was still modest in absolute terms. More interesting results come from the labor market and welfare participation. Using the New York sample, I find that the fraction of women who received benefits and stayed in New York in period 3 declined from 21.45% in the baseline level to 14.64% after the imposition of work requirements in New York. The percentage of women who stayed in New York and worked increased by 7 percentage points. These outcomes appear to be due to women shifting from welfare to full-time employment.

More importantly, using the New York sample I find that the impacts on the children of those women who would move out of New York in the presence of work requirements were large. After imposing work requirements in the New York sample, I identify a set of women who would have stayed in New York in the absence of work requirements but moved out as the requirements were imposed. In addition to changing their place of residence, these women also adjusted their welfare and labor supply decisions accordingly. A fraction of these women received better wage offers in their new place of residence and left AFDC to start working full-time while another sub-group of women received worse wage offers in their new destinations and shifted from part-time work to not working. Consequently, the probability of the women receiving benefits declined from 45.0% to 37.5% and the probability of the women working full-time increased from 53.8% to 62.5%. Given the finding that the more time spent in the labor market will reduce the direct time inputs in education production, the children whose mothers newly shifted from not working to working full-time might suffer considerably in terms of their achievement outcomes, holding other educational inputs constant. Moving out of New York might further hurt these children as they migrated into school districts with worse qualities than those in New York. On average, as illustrated in Figure 1, their children's achievement test scores fell by 3.5 percentile points because of their mothers' new relocation and labor supply decisions.

C. Simulations of Changes in the Labor Market

To study the impacts of a change in the labor market, I increase the discretized wage rates by 20% in either New York or Massachusetts.

In the New York sample, I find women's welfare participation modestly responded to the wage raise. More women, in addition, started working and working full-time. In the AFDC sample, the welfare enrollment rate dropped less than 1 percentage point, while responses in the labor market were much smaller than those in the New York sample. An interpretation of the different responses in labor supply is that women in AFDC sample tended to have worse wage draws and/or bad tastes for work.

D. Simulations of Effects of Tax Policies

The goal of these simulations is to trace out the impacts of the Earned Income Tax Credit (EITC) program on women's work, welfare and migration behaviors. Similar to the federal EITC program, this tax credit can be used to offset tax liabilities or, for credit amounts in excess of income tax liability, to provide refunds. The amount of the credit depends primarily on the level of earnings and the number of children in the family. The detailed description of this program is reported in Appendix E.

When introduced in New York this program appeared to be quite attractive. I find the out-migration rate declined by 0.4 percentage point in the New York sample and 0.3 percentage point in the AFDC sample. In the New York sample, labor force participation rate rose from 71.7% to 73.8% and the fraction of full-time workers in all workers rose from 51.5% to 52.5%.

From Massachusetts's perspective, introducing this program to Massachusetts did not induce a considerable amount of in-migration from New York. However, the percentage of women who did move into Massachusetts and work increased from 4.01% to 4.26%, which represented a 6% increase in the number of these women.

Discussion

These are preliminary results so the estimated effects should be interpreted cautiously. I have conducted sensitivity tests regarding the definitions of part-time and full-time workers, the size of sampled locations, the size of discretized achievement scores, and the size of discretized wage offers. I find the current estimates are robust to these tests. In this paper, the measure of whether someone received AFDC benefits was based on the mother's self-report about welfare receipt during the past year. This measure does not capture the variation of welfare spells among recipients within the given year. According to the eligibility rule used in this paper, 394 of 12387 data points (about 3%) in this study were not eligible but received AFDC benefits in a given year. I have conducted a sensitivity test by increasing the needs standard to the highest level in the nation and this finding persists. Considering the fact that AFDC benefits were provided on a monthly basis, it is possible that certain individuals were eligible in some months within a year but were not eligible if judged by their yearly incomes. Modeling monthly welfare receipt can help address this issue but it is out of the scope of this study, due to data limitations. In the model estimation, these observations are recoded to be non-recipients. The self-reported welfare participation formation might also be subject to the person's willingness and ability to provide this information. However, Harris (1993) compares administrative data with mother's self-report of welfare receipt and finds that this self-reported information is fairly accurate.

A limitation of the current model specification is that it does not allow women to learn from their past. In particular, it is assumed that women do not update their knowledge about the wage distribution in the current place of residence and the match between current school districts and their children. Nevertheless, the model used in this study characterizes important relationships in the decision-making processes of interest and is also adaptable to incorporating more realistic elements. The empirical model in this paper assumes fathers' labor income to be exogenous. This assumption does not take into account the variation of fathers' wage rates across different localities. In an immediate extension to this study, I will model stochastic wage distributions for fathers.

One further issue bearing discussion is welfare reform. In 1996, PRWORA replaced AFDC with the Temporary Assistance to Needy Families (TANF) program. There are three important differences between AFDC and TANF. First, AFDC entitled states to open-ended federal funds; the federal government was always obligated to match state dollars. Oppositely, TANF is a frozen or near-frozen funding stream. Second, TANF imposes stricter work requirements among welfare recipients than AFDC. Third, TANF newly stipulates a five-year lifetime limit on receipt of benefits. The simulation experiments in this paper are able to help understand how individuals' work, welfare, and migration behaviors respond to reduced benefit levels and the imposition of work requirements and how these responses impact their children's achievement outcomes. As for time limits, the economic model used in this study does not impose a constraint on maximum years of recipiency. Among seven waves of data used in this study, only one wave (1998) was collected after the passage of PRWORA. I have conducted a sensitivity test by excluding observations from 1998 interview and I find that the estimates are not themselves subject to concerns regarding the imposition of time limits. In further extensions to my study I will explicitly model forward-looking behaviors and incorporate new data in a bid to address time limits under TANF.

6 Conclusions

This paper provides a promising approach for analyzing how a woman's migration, welfare, and labor supply behaviors respond to changes in welfare policies and labor market conditions, recognizing that these behavioral changes could influence her child's achievement outcomes. Preliminary results in this paper have shown that through altering parental migration and work behaviors these welfare policy changes have important impacts on at-risk children's achievement outcomes.

A limitation of current structural approaches in the welfare migration literature is that specifying an incomplete choice set faced by individuals might omit other important migration determinants and, in turn, produce biased estimates. Estimating the educational production function as part of a structural model significantly enriches the choice set faced by single mothers who have to make migration decisions for their families. Modeling work and welfare participation decisions further helps identify different incentives for migration. Additionally, this paper allows households to choose from all counties in the United States in a bid to measure local characteristics more accurately.

Simulations conducted by this study permit a focused view of women's behavioral responses to a series of changes in welfare policies and labor market conditions. This paper finds that the migration directly induced by welfare differentials is modest as a component of the general migration flow. In practice, people migrate for economic reasons as well as non-economic reasons. Nevertheless, poor and low-educated single women with children do change their residential locations in response to changes in welfare policies and labor market conditions. In several simulation experiments, the induced out-migration is small but statistically significant. More important are the impacts on the groups affected by policies. Those at-risk often are significantly affected. For example, increases in a state's welfare benefits can significantly increase the fraction of in-migrants who newly decide to enter welfare. Similarly, the impacts on the children of those women who would move out of a state in the presence of work requirements are large. On average, using New York as an example, their children's achievement test scores would fall by 3.5 percentile points because of their mothers' new relocation and labor supply decisions.

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Appendixes

Appendix A Summaries of Major Data Sources.

1. The National Longitudinal Survey of Youth

   The original NLSY began in 1979 with a national sample of 12686 young adults between the ages of 14 and 21. It included a nationally representative sample of 6,111 youths, an over-sample of 5,295 blacks, Hispanics, and economically disadvantaged whites, and a supplemental sample of 1,280 persons in the military in September 1978. Interviews with the military sub-sample were suspended after 1984 and for economically disadvantaged non-Hispanic whites after 1990. In this study, I select mothers who had mother-child data from 1986 to 1998 and exclude those economically disadvantage non-Hispanic whites.

2. The National Longitudinal Survey of Youth - Children Sample

   Beginning in 1986, the NLSY-Child collected data on all of the children born to the female NLSY respondents. The NLSY - Child sample (through 1998) supplies data on children with mothers between the ages of 33 and 40 at the end of 1997. Children under the age of 15 comprise the majority of this sample. The NLSY - Child contains a set of cognitive and behavioral assessments. The NLSY - Child sample biennially interviews both mother and child.

3. Census of Population and Housing, 1990 [United States]: Public Use MicroData Sample: 5-percent Sample

   To construct relative measurements of teacher salary and expenditure per pupil, I select college-graduated white males, who were between 27 and 40 years old and working full-time (30+ hours a week and 45+ weeks a year). In this selected sample, the relative median teacher salary in a county is calculated by dividing the median annual wage income of male public non-postsecondary teachers with the median annual wage income of males with occupations other than these teachers. These non-postsecondary teachers include pre-kindergarten and kindergarten teachers, elementary school teachers, and secondary school teachers. Similarly, the relative expenditure per pupil is measured by the nominal expenditure per pupil relative to the median annual wage income of all males in the selected MicroData sample.

   The empirical model also uses the median wage rates of females in this data set by age, education attainment, and ethnic groups. These median wage rates are treated as important elements of local wage distribution.

4. National Center for Education Statistics(NCES): The Common Core Data(CCD)

   This a comprehensive, annual, national statistical database of information concerning all public elementary and secondary schools (approximately 95,000) and school districts (approximately 17,000). In particular, I average the grade-specific school characteristics used in the estimation to the county level.

Appendix B. Formulas of welfare benefits

The rule of yearly AFDC benefit is simplified and given as follows (Keane and Moffitt, 1996):

$$B_a = \begin{cases} Min\{P_m, r[P_s - Max(0, wh + y - D)]\} & \text{if } wh + y < P_n \text{ and } h \neq 2 \\ 0 & \text{if otherwise,} \end{cases}$$

where B_a is the AFDC benefits received by individuals, P_m is the maximum amount paid, r is the "ratable reduction," P_s is the payment standard, wh is wage income, y is non-labor income, D is the permitted deductible, and P_n is the needs standard. The variables P_m, P_s, P_n, and r vary by state, year, and family size. The eligibility data used in the estimation are obtained from the Urban Institute and Robert Moffitt at the Johns Hopkins University.

Appendix C. Income tax liabilities

The values of federal and state income taxes are obtained from NBER's TAXSIM program, which calculates liabilities under US Federal and State income tax laws from individual data.

To prepare the income taxes used by the computer program in the paper, I generate a data matrix with 100 income levels, 2 marital statuses, and 4 family sizes for each state. The TAXSIM program then simulates the income tax liabilities for each cell in the data matrix in all states from 1986 to 1998.

Appendix D. Deriving the probability of location choices with random sampling

Let $C = \{1, \ldots, K\}$ denote the full choice set, and $D_t(k_t) \subseteq C$ a subset. Subset $D_t(k_t)$ consists of k_t plus a sample of $\widetilde{K} - 1$ alternative elements from C, drawn with probability p. The sampling method of selecting the chosen alternative plus $\widetilde{K} - 1$ non-chosen alternatives drawn at random satisfies

$$\pi(D_t(k_t)|k_t, \Omega_t, \mu) = \begin{cases} p^{\widetilde{K}-1}(1-p)^{K-\widetilde{K}} & \text{if } D_t(k_t) = \{k_t, \ldots\} \subseteq C \\ 0 & \text{otherwise,} \end{cases}$$

where $\pi(D_t(k_t)|k_t, \Omega_t, \mu)$ denotes the probability that the subset $D_t(k_t)$ will be drawn, given the observed choice, k_t, and the vector of state variables, Ω_t.

Hence, the equation (17) is written as follows

$$\begin{aligned} \Pr(k_t &= \kappa^*|\Omega_t, \mu) \\ &= \frac{\exp\left\{\frac{\widetilde{V}(\Omega_t,\mu|\kappa^*)}{b_2} + \ln \pi\left[D_t(\kappa^*)|\kappa^*, \Omega_t, \mu\right]\right\}}{\sum\limits_{\kappa' \in D_t(\kappa^*)} \exp\left\{\frac{\widetilde{V}(\Omega_t,\mu|\kappa')}{b_2} + \ln \pi\left[D_t(\kappa')|\kappa', \Omega_t, \mu\right]\right\}}. \end{aligned} \tag{21}$$

Since this study adopts a random sampling method and π is the same for all $k' \in D_t(\kappa^*)$, the terms involving π cancel out of the above expression.

Appendix E. EITC program used in Section 5

This program has three distinct ranges, depending on the income of the worker:

In the subsidy range, each additional dollar of income is supplemented by the credit. As workers earn an additional dollar of income, their credit increases by 40 cents, up to a maximum credit of \$3,000. In particular, the subsidy range extends up to earnings of \$7,500 for a family with one child.

In the flat range, workers earning between \$7,500 and \$9,500 receive the maximum credit of \$3,000. In this range, increased earnings do not change the credit amount.

In the phase-out range, the credit is gradually reduced, or phased out, as workers' earnings increase. The phase-out range starts at \$9,500 in annual earnings. As workers earn more than this amount, the credit is phased out at a rate of 21 cents per dollar earned.

Table 1

Summary Statistics
Number of Mother/Child pairs: 5377
Number of Person-Years: 12387

Variable	Mean	Standard deviation
Age of mother	33.5	3.41
Age of child	10.5	2.20
Married	0.58	0.49
High school	0.48	0.50
More than high school	0.33	0.47
Non-white	0.57	0.50
Boy	0.50	0.50
Dropout rate for 11th graders	0.06	0.01
Teacher salary(1)	0.80	0.18
Expenditure per pupil(1)	0.12	0.04
Teacher-student ratio	0.06	0.01
Percentage of white in school	0.59	0.28
Yearly housing cost(2)	0.51	0.14
Move	0.11	0.32
Non-labor income(2)	1.94	2.46
Net income(2)	1.63	2.02
Hourly wage rate(3)	0.88	0.66
Local median hourly wage rate(3)	0.98	0.42
Part-time work(4)	0.31	0.46
Full-time work(4)	0.44	0.50
PIAT Math score	0.50	0.29
# of young children in HH (0-5)	0.50	0.73
# of old children in HH (6-17)	2.18	1.09
Mother's AFQT score	0.45	0.28

Notes:

(1) Measured as a proportion of yearly income of college-graduated prime-aged males. See appendix for details.
(2) In $10,000's of 1990 dollars.
(3) In $10's of 1990 dollars.
(4) See appendix for the definition of part-time and full-time workers.

Table 2

Distribution of the sample by labor supply and program participations
(Sample size: 12387 person years)

	Not eligible	Eligible	
		No AFDC	AFDC
Non-workers			
Counts	1955	263	864
Row percent	64.6%	8.4%	28.0%
Column percent	22.2%	11.9%	62.4%
Mean age	33.4 (3.47)	34.0 (3.45)	32.0 (3.08)
Mean non-labor income	2.96 (3.51)	0.06 (0.13)	0.05 (0.15)
High school completion	0.71 (0.45)	0.57 (0.50)	0.55 (0.50)
Mean wage rate	9.42 (3.86)	8.93 (3.76)	8.51 (4.25)
Mean child math score	0.48 (0.29)	0.34 (0.25)	0.36 (0.27)
Part-time workers			
Counts	2846	497	520
Row percent	73.7%	12.8%	13.5%
Column percent	32.4%	22.5%	37.6%
Mean age	33.6 (3.40)	33.3 (3.43)	32.0 (3.34)
Mean non-labor income	2.88 (2.66)	0.08 (0.15)	0.04 (0.12)
High school completion	0.84 (0.37)	0.79 (0.41)	0.66 (0.47)
Mean wage rate	9.09 (8.82)	9.44 (9.42)	6.58 (6.49)
Mean child math score	0.55 (0.29)	0.43 (0.28)	0.42 (0.27)
Full-time workers			
Counts	3997	1445	–
Row percent	73.5%	26.5%	–
Column percent	45.4%	65.5%	–
Mean age	33.9 (3.30)	33.5 (3.43)	–
Mean non-labor income	2.44 (1.78)	0.08 (0.14)	–
High school completion	0.91 (0.28)	0.86 (0.34)	–
Mean wage rate	8.84 (6.45)	7.74 (4.55)	–
Mean child math score	0.53 (0.28)	0.47 (0.27)	–

Table 3a

Parameter Estimates from the Full model
Educational Production Function

Variable	Point estimate	Std. Error [1]
Intercept	–0.2932	0.4544
Child age (in 10 years)	–0.2246	0.6238
Child age (in 10 years) squared	0.2110	0.2820
Age of mother (in 10 years)	–0.1583	0.0368
Married	0.2173	0.0263
High school	0.2324	0.0311
More than high school	0.3574	0.0398
Non-white	–0.3283	0.0304
Boy	0.0782	0.0234
Dropout rate for 11th graders	–0.4694	2.8908
Expenditure per pupil	–0.4799	0.7273
Teacher salary	–0.3532	0.1700
Teacher/pupil ratio	–1.0191	3.1008
Percentage of white in schools	–0.2627	0.1133
Dropout rate × Log(P-p) [2]	0.9412	1.2030
Expenditure per pupil × Log(P-p)	0.1257	0.2947
Teacher salary × Log(P-p)	0.1456	0.0730
Teacher/pupil ratio × Log(P-p)	–2.2091	1.3488
Percentage of white in school × Log(P-p)	0.0881	0.0479
Part-time × Log(P-p)	–0.1050	0.0235
Full-time × Log(P-p)	–0.1872	0.0381
Dropout rate × Child age	–1.3529	1.5679
Expenditure per pupil × Child age	0.4278	0.4213
Teacher salary × Child age	–0.0060	0.0817
Teacher/pupil ratio × Child age	1.3302	1.7618
Percentage of white in school × Child age	–0.0051	0.0661
Part-time × Child age	0.0019	0.0027
Full-time × Child age	0.0159	0.0044
Move	0.0509	0.0378
Part-time	0.2237	0.0501
Full-time	0.4309	0.0873
Consumption (in $10,000 's)	–0.0052	0.0021
Loading on 1st order heterogeneity factor	4.0322	0.3365
Loading on 2nd order heterogeneity factor	–6.9682	0.8689
Loading on 3rd order heterogeneity factor	0.9375	0.5731
Mother's AFQT score	0.6070	0.1187
Mother's AFQT score × Log(P-p)	0.8727	0.0730
1st order	–7.9161	0.2888
2nd order	–15.2012	0.4723
3rd order	–10.1654	0.3116
4th order	–2.0958	0.0680

Note: (1) All standard errors are robust standard errors.
(2) P is the highest level of discretized scores and p is any given discretized score level.

Table 3b

Parameter Estimates from the Full model
Utility Function Parameters

Variable	Point estimate	Std. Error [(2)]
Intercept in reserve consumption	2.4431	1.2883
1st order heterogeneity factor loading in reserve function	3.1937	1.2859
2nd order heterogeneity factor loading in reserve function	−2.7419	1.1743
Power of consumption	−0.3275	0.5182
Scale on child's score / mother's AFQT score	15.4081	18.3330
Reserve child's score / mother's AFQT score	−0.0210	0.0134
Power of child's score / mother's AFQT score	−0.1347	0.0230
Intercept in disutility of any work	−0.9480	1.1585
1st order heterogeneity factor loading in disutility of any work	−5.6954	1.9747
2nd order heterogeneity factor loading in disutility of any work	−0.6822	7.4220
3rd order heterogeneity factor loading in disutility of any work	4.4066	5.4998
# of young kids (0-5) in disutility of any work	0.3857	0.0536
# of old kids (6-17) in disutility of any work	0.0751	0.0231
Intercept in disutility of full-time work	0.2967	7.5488
1st order heterogeneity factor loading in disutil of full-time work	−3.4671	40.5895
2nd order heterogeneity factor loading in disutil of full-time work	−2.6330	66.4190
3rd order heterogeneity factor loading in disutil of full-time work	4.6927	33.2144
# of young kids (0-5) in disutil of full-time work	0.2041	0.0220
# of old kids (6-17) in disutil of full-time work	0.1199	0.0136
Moving psychic cost	−4.9308	6.0020
Moving psychic cost (across states)	−2.1090	2.5719
Moving psychic cost (across regions)	−0.8085	0.9869
Inverse of parameter **b** in Gumbel error on work/welfare choice	7.4585	8.6336
Inverse of parameter **b** in Gumbel error on location choice	1.4830	1.8077
Dummy for Census region – Midwest [(1)]	−0.2910	0.3753
Dummy for Census region – South	−0.3157	0.4016
Dummy for Census region –West	−0.2102	0.2830
Welfare stigma	−0.0238	0.0284

Note: (1) Northeast is the base region.
(2) All standard errors are robust standard errors.

Table 3c

Parameter Estimates from the Full model
Wage Function

Variable	Point estimate	Std. Error (1)
Intercept	–3.9603	0.1929
Local wage rate	0.8903	0.1586
Local wage rate squared	–0.3340	0.0447
Local wage rate × Heterogeneity factor	0.5840	0.1844
High school	0.5071	0.0493
More than high school	0.7593	0.0590
Non-white	0.3598	0.0321
Mother's AFQT score	1.7825	0.1613
Mother's AFQT score × Log(*G*-*g*) (2)	–0.2775	0.1681
Loading on 1st order heterogeneity factor	–2.3666	0.3638
Loading on 2nd order heterogeneity factor	1.3898	0.2463
1st order of baseline hazard [Log(*G*-*g*)]	–4.1171	0.3839
2nd order of baseline hazard [Log(*G*-*g*)]^2	–4.0687	0.6380
3rd order of baseline hazard [Log(*G*-*g*)]^3	–2.8639	0.3026

Note: (1) All standard errors are robust standard errors.
(2) *G* is the highest level of discretized wage rates; *g* is any given discretized wage rate level.

Table 3d

Parameter Estimates from the Full model:
Those Defining the Probabilities for the Heterogeneity Points

Variable	Point estimate	Std. Error (1)
Probability parameter at 0	1.2191	0.0462
Probability parameter at 1/3	–1.9992	0.1322
Probability parameter at 2/3	2.8025	0.1628

Note: (1) All standard errors are robust standard errors.

Table 3e

Probability distribution of Heterogeneity Types

Heterogeneity factor	Probability
0	0.1108
1/3	0.2393
2/3	0.3287
1	0.3212

Table 3f

Production Function Estimates of
Marginal Effects with Comparisons to OLS and
“Hazard” models without Endogeneity Controls [1]

Variable	Marginal effects: OLS	Production function only (no endogeneity Controls)	Full model (with selection and endogeneity controls)
Age of mother	–0.027	–0.031	–0.026
	(0.007)	(0.005)	(0.005)
Age of child	0.063	0.070	0.074
	(0.011)	(0.014)	(0.011)
Married	0.018	0.011	0.023
	(0.005)	(0.004)	(0.004)
High school (mother)	0.040	0.029	0.004
	(0.007)	(0.004)	(0.004)
More than high school	0.058	0.051	0.020
	(0.008)	(0.005)	(0.005)
Non-white	–0.058	–0.052	–0.050
	(0.006)	(0.005)	(0.005)
Boy	0.013	0.013	0.008
	(0.005)	(0.003)	(0.003)
Dropout rate	–1.025	–0.908	–0.166
	(0.251)	(0.193)	(0.077)
Expenditure per pupil	0.135	0.121	0.023
	(0.063)	(0.046)	(0.015)
Teacher salary	–0.013	–0.002	–0.009
	(0.014)	(0.0130	(0.004)
Teacher/student ratio	0.713	0.785	–0.566
	(0.224)	(0.192)	(0.138)
Percentage of white	–0.019	–0.012	–0.016
	(0.010)	(0.007)	(0.005)
Move	0.017	0.015	0.015
	(0.007)	(0.006)	(0.006)
Part-time work	0.028	0.035	–0.004
	(0.006)	(0.006)	(0.001)
Full-time work	0.011	0.031	–0.017
	(0.006)	(0.005)	(0.004)
Net income	0.012	0.010	0.000
	(0.002)	(0.001)	(0.000)
AFQT score (mom’s)	0.282	0.269	0.273
	(0.012)	(0.006)	(0.006)
Intercept	0.365	–	–
	(0.037)	–	–

Note: (1) Standard errors of marginal impacts are in parentheses.

Tables 4a-b Simulation within Sample

Table 4a
Goodness of Fit
(sample size: 12387 person years)

	Observed	Simulated
AFDC recipients		
Counts	1384 (11.17%)	1363 (11.03%)
Child outcomes		
Mean score	0.497 (0.285[(1)])	0.497 (0.245[(1)])
Work status		
Any work	9305 (75.1%)	9427 (76.1%)
Full-time	5442 (58.5%[(2)])	5590 (59.4%[(2)])
Migration		
Moves	1403	1632
Moves per mover	1.25	1.62

Notes: (1) Standard deviation is in parentheses.
(2) Percentage of full-time workers among workers is in parentheses.

Table 4b
(sample size: 12387 person years)

	AFDC	Workers	Full-time among workers	Mean scores
Baseline	11.0%	76.1%	59.4%	0.497
Increase the AFDC benefits by 30%	11.8%	75.8%	59.1%	0.497
Introduce strict work requirements	7.5%	79.3%	58.0%	0.497
Increase wage rates by 20%	10.6%	77.1%	59.7%	0.498
Introduce the EITC	11.0%	76.2%	59.3%	0.497

Tables 5a-c

Simulation I - Location choices for women
who reside in New York in the first period
(New York sample: 9306)

Table 5a

After two periods	100(%) women originated from New York			
	Stay in NY	Move to MA	Move to rest of U.S.	Induced migration [1]
1. Baseline	84.61	4.56	10.83	–
2. Decrease the AFDC benefits in NY by 30%	84.48	4.60	10.92	0.13 (0.12)
3. Increase the AFDC benefits in MA by 30%	84.57	4.62	10.81	0.04 (0.04)
4. Strict work requirements in NY	84.18	4.71	11.11	0.43 (0.49)
5. Strict work requirements in MA	84.70	4.44	10.86	–0.09 (1.19)
6. Increase wage rate in NY by 20%	84.91	4.47	10.62	–0.30 (0.23)
7. Increase wage rate in MA by 20%	84.53	4.67	10.80	0.08 (0.06)
8. Introduce EITC to NY	85.01	4.45	10.54	–0.40 (0.26)
9. Introduce EITC to MA	84.50	4.71	10.79	0.11 (0.08)

Note: (1). Induced migration is defined as the additional out-migration after policy changes in New York. Standard errors of induced migration rates are in parentheses.

Table 5b

After two periods	100(%) women originated from New York		
	Stay in NY and on AFDC	Move to MA and on AFDC	Move to rest of U.S. and on AFDC
1. Baseline	21.45	1.07	2.54
2. Decrease the AFDC benefits in NY by 30%	19.07	1.07	2.57
3. Increase the AFDC benefits in MA by 30%	21.45	1.23	2.53
4. Strict work requirements in NY	14.64	1.14	2.63
5. Strict work requirements in MA	21.47	0.78	2.54
6. Increase wage rate in NY by 20%	20.57	1.06	2.49
7. Increase wage rate in MA by 20%	21.44	1.06	2.53
8. Introduce EITC to NY	20.76	1.05	2.49
9. Introduce EITC to MA	21.44	1.05	2.53

Table 5c

After two periods	100(%) women originated from New York		
	Stay in NY and work	Move to MA and work	Move to rest of U.S. and work
1. Baseline	71.71	4.01	9.20
2. Decrease the AFDC benefits in NY by 30%	72.64	4.04	9.25
3. Increase the AFDC benefits in MA by 30%	71.67	3.98	9.18
4. Strict work requirements in NY	78.29	4.07	9.39
5. Strict work requirements in MA	71.77	4.28	9.22
6. Increase wage rate in NY by 20%	73.33	3.92	9.02
7. Increase wage rate in MA by 20%	71.63	4.19	9.17
8. Introduce EITC to NY	73.87	3.91	8.94
9. Introduce EITC to MA	71.61	4.26	9.16

Tables 6a-c

Simulation II - Location choices for women
who reside in New York and participate AFDC in the first period
(New York AFDC sample: 2680)

Table 6a

After two periods	100(%) women originated from New York			
	Stay in NY	Move to MA	Move to rest of U.S.	Induced migration [1]
1. Baseline	84.25	4.55	11.19	–
2. Decrease the AFDC benefits in NY by 30%	84.03	4.63	11.34	0.22 (0.15)
3. Increase the AFDC benefits in MA by 30%	84.18	4.63	11.19	0.07 (0.03)
4. Strict work requirements in NY	83.36	4.85	11.79	0.89 (0.51)
5. Strict work requirements in MA	84.33	4.48	11.19	–0.08 (1.39)
6. Increase wage rate in NY by 20%	84.40	4.51	11.08	–0.15 (0.25)
7. Increase wage rate in MA by 20%	84.14	4.66	11.19	0.11 (0.06)
8. Introduce EITC to NY	84.55	4.44	11.01	–0.30 (0.28)
9. Introduce EITC to MA	84.14	4.66	11.19	0.11 (0.08)

Note: (1). Induced migration is defined as the additional out-migration after policy changes in New York.
Standard errors of induced migration rates are in parentheses.

Table 6b

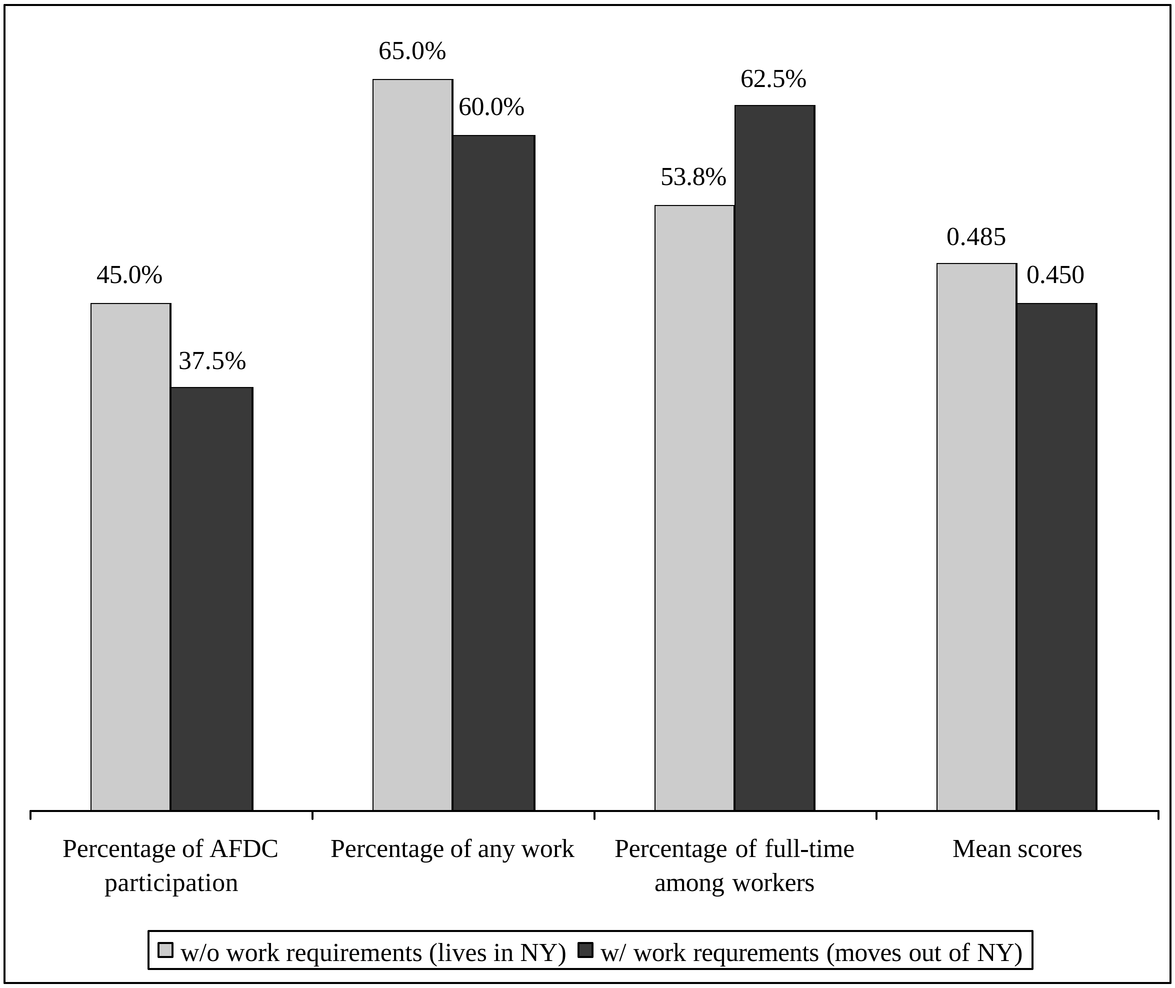
After two periods	100(%) women originated from New York		
	Stay in NY and on AFDC	Move to MA and on AFDC	Move to rest of U.S. and on AFDC
1. Baseline	31.16	1.49	3.69
2. Decrease the AFDC benefits in NY by 30%	27.99	1.49	3.54
3. Increase the AFDC benefits in MA by 30%	31.16	1.60	3.69
4. Strict work requirements in NY	19.55	1.64	3.36
5. Strict work requirements in MA	31.19	1.08	3.69
6. Increase wage rate in NY by 20%	30.30	1.49	3.58
7. Increase wage rate in MA by 20%	31.16	1.42	3.69
8. Introduce EITC to NY	30.37	1.46	3.66
9. Introduce EITC to MA	31.16	1.42	3.69

Table 6c

After two periods	100(%) women originated from New York		
	Stay in NY and work	Move to MA and work	Move to rest of U.S. and work
1. Baseline	61.90	3.73	8.21
2. Decrease the AFDC benefits in NY by 30%	63.10	3.77	8.28
3. Increase the AFDC benefits in MA by 30%	61.87	3.66	8.21
4. Strict work requirements in NY	72.20	3.81	8.54
5. Strict work requirements in MA	61.94	4.33	8.21
6. Increase wage rate in NY by 20%	63.99	3.69	8.13
7. Increase wage rate in MA by 20%	61.83	3.84	8.21
8. Introduce EITC to NY	65.19	3.66	8.06
9. Introduce EITC to MA	61.83	3.96	8.21

Figure 1

Changes in women's choices and consequent children's scores
when New York imposes strict work requirements
(sample: women who would leave NY in the presence of work requirements)



Appendix Table 1-3 to Table 5a-c, 6a-c

Appendix Table 1
Comparisons of New York, Massachusetts, and other locations
(1990 data)

	New York	Massachusetts	NE excluding NY&MA	Rest of US excluding NY&MA
1. Median tax rate among the first income quartiles	1.8%	3.6%	0.6%	1.9%
2. AFDC maximum payments for family of 2	$5616	$5832	$5286	$3516
3. Median rent	$5736	$7440	$6264	$4956
4. Median wage rate among non-white low-educated women aged 33-39	$8.0	$8.6	$7.9	$6.5
5. Median dropout rate for 11th graders	5.7%	6.4%	5.7%	6.2%
6. Median relative expenditure per pupil in public K-12 schools	17.2%.	13.2%	17.9%	12.0%

Appendix Table 2
(New York sample: 9306)

Place of residence after two periods		(1) AFDC participation	(2) Workers	(3) Full-time among workers	(4) Mean scores
1. Baseline					
New York	% of original NY sample	21.45	71.71	51.50	0.459
	% of currently in NY	25.4	84.8	71.8	(0.067)
Massachusetts	% of original NY sample	1.07	4.01	2.99	0.474
	% of currently in MA	23.6	88.0	74.5	(0.048)
Rest of U.S.	% of original NY sample	2.54	9.20	6.71	0.463
	% of currently in rest of U.S.	23.4	84.9	72.9	(0.029)
2. Decrease benefits in NY by 30%					
New York	% of original NY sample	19.07	72.64	52.87	0.460
	% of currently in NY	22.6	86.0	72.8	(0.067)
Massachusetts	% of original NY sample	1.07	4.04	3.02	0.473
	% of currently in MA	23.4	87.9	74.7	(0.048)
Rest of U.S.	% of original NY sample	2.57	9.25	6.74	0.463
	% of currently in rest of U.S.	23.5	84.7	72.8%	(0.029)
3. Increase benefits in MA by 30%					
New York	% of original NY sample	21.45	71.67	51.47	0.459
	% of currently in NY	25.4	84.8	71.8	(0.067)
Massachusetts	% of original NY sample	1.23	3.98	2.97	0.472
	% of currently in MA	26.5	86.1	74.6	(0.050)
Rest of U.S.	% of original NY sample	2.53	9.18	6.69	0.464
	% of currently in rest of U.S.	23.4	84.9	73.0	(0.029)
4. Strict work requirements in NY					
New York	% of original NY sample	14.64	78.29	54.10	0.460
	% of currently in NY	17.4	93.0	69.1	(0.076)

Massachusetts	% of original NY sample	1.14	4.07	3.05	0.474
	% of currently in MA	24.2	86.5	74.9	(0.045)
Rest of U.S.	% of original NY sample	2.63	9.39	6.80	0.462
	% of currently in rest of U.S.	23.7	84.5	72.4	(0.029)
5. Strict work requirements in MA					
New York	% of original NY sample	21.47	71.77	51.56	0.459
	% of currently in NY	25.4	84.7	71.8	(0.067)
Massachusetts	% of original NY sample	0.78	4.28	3.11	0.473
	% of currently in MA	17.7	96.4	72.6	(0.048)
Rest of U.S.	% of original NY sample	2.54	9.22	6.73	0.462
	% of currently in rest of U.S.	23.3	84.9	73.0	(0.029)
6. Increase wage rate in NY by 20%					
New York	% of original NY sample	20.57	73.33	53.05	0.460
	% of currently in NY	24.2	86.4	72.4	(0.068)
Massachusetts	% of original NY sample	1.06	3.92	2.92	0.474
	% of currently in MA	23.8	97.7	74.5	(0.048)
Rest of U.S.	% of original NY sample	2.49	9.02	6.58	0.466
	% of currently in rest of U.S.	23.5	84.9	72.9	(0.098)
7. Increase wage rate in MA by 20%					
New York	% of original NY sample	21.44	71.63	51.44	0.459
	% of currently in NY	25.4	84.7	71.8	(0.067)
Massachusetts	% of original NY sample	1.06	4.19	3.13	0.474
	% of currently in MA	22.8	89.7	74.6	(0.051)
Rest of U.S.	% of original NY sample	2.53	9.17	6.68	0.463
	% of currently in rest of U.S.	23.4	84.9	72.9	(0.029)
8. EITC in NY					
New York	% of original NY sample	20.76	73.87	52.51	0.460
	% of currently in NY	24.4	86.9	71.1	(0.068)
Massachusetts	% of original NY sample	1.05	3.91	2.91	0.476
	% of currently in MA	23.7	87.9	74.5	(0.048)
Rest of U.S.	% of original NY sample	2.49	8.94	6.52	0.466
	% of currently in rest of U.S.	23.7	84.8	73.0	(0.029)
9. EITC in MA					
New York	% of original NY sample	21.44	71.61	51.54	0.459
	% of currently in NY	25.4	84.7	71.8	(0.067)
Massachusetts	% of original NY sample	1.05	4.26	3.16	0.476
	% of currently in MA	22.4	90.4	74.2	(0.051)
Rest of U.S.	% of original NY sample	2.53	9.16	6.67	0.463
	% of currently in rest of U.S.	23.4	84.9	72.9	(0.029)

Note: Top figure in each cell of columns (1)-(3) is the percentage among the full New York sample; bottom figure in each cell of columns (1)-(3) is the percentage among the observations residing in the location given at the beginning of the row. Top figure in each cell of column (4) is the mean of their children's scores; bottom figure in each cell of column (4) is the standard error of the mean score.

Appendix Table 3
(New York AFDC sample: 2680)

Place of residence after two periods		(1) AFDC participation	(2) Workers	(3) Full-time among workers	(4) Mean scores
1. Baseline					
New York	% of original NY sample	31.16	61.90	37.46	0.465
	% of currently in NY	37.0	73.5	60.5	(0.083)
Massachusetts	% of original NY sample	1.49	3.73	2.50	0.512
	% of currently in MA	32.8	82.0	67.0	(0.092)
Rest of U.S.	% of original NY sample	3.69	8.21	5.30	0.474
	% of currently in rest of U.S.	33.0	73.3	64.6	(0.030)
2. Decrease benefits in NY by 30%					
New York	% of original NY sample	27.99	63.10	38.62	0.465
	% of currently in NY	33.3	75.1	61.2	(0.085)
Massachusetts	% of original NY sample	1.49	3.77	2.54	0.512
	% of currently in MA	32.3	81.5	67.3	(0.092)
Rest of U.S.	% of original NY sample	3.54	8.28	5.34	0.471
	% of currently in rest of U.S.	31.3	73.0	64.4	(0.030)
3. Increase benefits in MA by 30%					
New York	% of original NY sample	31.16	61.87	37.43	0.464
	% of currently in NY	37.0	73.5	60.5	(0.083)
Massachusetts	% of original NY sample	1.60	3.66	2.54	0.512
	% of currently in MA	34.7	79.0	69.4	(0.096)
Rest of U.S.	% of original NY sample	3.69	8.21	5.30	0.474
	% of currently in rest of U.S.	33.0	73.3	64.6	(0.030)
4. Strict work requirements in NY					
New York	% of original NY sample	19.55	72.20	39.40	0.465
	% of currently in NY	23.5	86.6	54.6	(0.098)
Massachusetts	% of original NY sample	1.64	3.81	2.57	0.502
	% of currently in MA	33.9	78.5	67.7	(0.086)
Rest of U.S.	% of original NY sample	3.36	8.54	5.37	0.466
	% of currently in rest of U.S.	28.5	72.5	62.9	(0.031)
5. Strict work requirements in MA					
New York	% of original NY sample	31.19	61.94	37.46	0.465
	% of currently in NY	37.0	73.5	60.5	(0.083)
Massachusetts	% of original NY sample	1.08	4.33	2.72	0.523
	% of currently in MA	24.2	96.7	63.0	(0.097)
Rest of U.S.	% of original NY sample	3.69	8.21	8.21	0.474
	% of currently in rest of U.S.	33.0	73.3	64.6	(0.029)
6. Increase wage rate in NY by 20%					
New York	% of original NY sample	30.30	63.99	38.77	0.465
	% of currently in NY	35.9	75.8	60.6	(0.083)

Massachusetts	% of original NY sample	1.49	3.69	2.50	0.519
	% of currently in MA	33.1	81.8	67.7	(0.096)
Rest of U.S.	% of original NY sample	3.58	8.13	5.26	0.473
	% of currently in rest of U.S.	32.3	73.4	64.7	(0.099)
7. Increase wage rate in MA by 20%					
New York	% of original NY sample	31.16	61.83	37.39	0.464
	% of currently in NY	37.0	73.5	60.5	(0.083)
Massachusetts	% of original NY sample	1.42	3.84	2.61	0.509
	% of currently in MA	30.4	82.4	68.0	(0.095)
Rest of U.S.	% of original NY sample	3.69	8.21	5.30	0.474
	% of currently in rest of U.S.	33.0	73.3	64.6	(0.030)
8. EITC in NY					
New York	% of original NY sample	30.37	65.19	38.28	0.465
	% of currently in NY	35.9	77.1	58.7	(0.083)
Massachusetts	% of original NY sample	1.46	3.66	2.46	0.526
	% of currently in MA	32.8	82.4	67.4	(0.095)
Rest of U.S.	% of original NY sample	3.66	8.06	5.22	0.473
	% of currently in rest of U.S.	33.2	73.2	64.8	(0.029)
9. EITC in MA					
New York	% of original NY sample	31.16	61.83	37.39	0.464
	% of currently in NY	37.0	73.5	60.5	(0.083)
Massachusetts	% of original NY sample	1.42	3.96	2.61	0.509
	% of currently in MA	30.4	84.8	66.0	(0.094)
Rest of U.S.	% of original NY sample	3.69	8.21	5.30	0.474
	% of currently in rest of U.S.	33.0	73.3	64.6	(0.030)

Note: Top figure in each cell of columns (1)-(3) is the percentage among the New York AFDC sample; bottom figure in each cell of columns (1)-(3) is the percentage among the observations residing in the location given at the beginning of the row. Top figure in each cell of column (4) is the mean of their children's scores; bottom figure in each cell of column (4) is the standard error of the mean score.