The Effects of Single Mothers' Welfare Participation and Work Decisions on Children's Attainments

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Abstract

This research examines the effects of mothers' welfare and work decisions on their children's attainments using a random effect instrumental variables (REIV) estimator. The estimator employs sibling comparisons in a random effect framework and an instrumental variables approach to address the unobserved heterogeneity that may influence mothers' work and welfare decisions. The identification comes from the variation in mothers' different economic incentives that arises from the AFDC benefit structures across U.S. states. I focus on children who were born to single mothers with twelve or fewer years of schooling. The short-run child attainments under consideration are the Peabody Individual Achievement Test math and reading recognition scores from the Children of the National Longitudinal Survey of Youth 1979 cohort. Long-run attainments are a child's number of years of schooling by age 25 and his or her early adulthood labor income, drawn from the Panel Study of Income Dynamics. The REIV estimates imply that, relative to no welfare participation, participating in welfare for one to three years provides up to a 5 percentage point gain in a child's Picture Individual Achievement Test (PIAT) scores. The negative effect of childhood welfare participation on adult earnings found by others is not significant if one accounts for mothers' work decisions. At the estimated values of the model parameters, a mother's number of years of work contributes between \$3,000 and \$7,000 1996 dollars to her child's labor income, but has no significant effect on the child's PIAT test scores. Finally, children's number of years of schooling are relatively unresponsive to mothers' work and welfare participation choices.

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1 Introduction

Poor families, many of them headed by single mothers, can choose to participate in various government welfare programs designed to improve the well-being of the family members. Before 1996, Aid to Families with Dependent Children (AFDC) was one of the largest among all such transfer programs.[1] In addition to offering cash benefits, participating in the AFDC program often assures a person's eligibility for other welfare programs such as the Food Stamps program and Medicaid.[2] Hence, participation in AFDC can be used as a rough measure of receiving welfare support from the government for single mothers to raising their offspring on their own.

Besides the importance of the AFDC program to needy families, we have only limited information on the causal relationship between a mother's welfare participation decisions and her child's attainments. Several important questions warrant investigation. First, previous studies find that AFDC participation exhibits a negative statistical relationship with all sorts of children's outcomes in the data. This relationship seems counterintuitive, since the provision of both cash and in-kind benefits from government programs presumably should have helped participating families to better educate their offspring.

Second, the AFDC program creates a strong work disincentive for participating mothers. Since the monetary AFDC benefit is a decreasing function of the amount of labor income a participating mother has earned, AFDC creates an implicit tax on participant's labor income. Furthermore, when losing the eligibility of other linked welfare programs is considered, the implicit tax rate of AFDC at the margin is well above 100% (Keane and Moffitt, 1996). As a result, welfare participants are often also associated with unemployment, or with working only enough to fulfil the minimum requirement.

[1] In 1996, the Personal Responsibility and Work Opportunity Reconciliation Act of 1996 (PROWORA) ended AFDC, replacing it with the new, Temporary Aid for Needy Families (TANF) program. TANF differs from AFDC in the sense that it ends the "entitlement" of eligible welfare families by introducing a time limit on welfare benefits and gives states more flexibility in developing their own programs.

[2] Keane and Moffitt (1998) state that, in 1984, 89% of AFDC recipients also received Food Stamps and Medicaid benefits, and another 42% also had a fourth benefit, mostly Housing Subsidies.

The effect of a mother's work on her child's attainment has long been recognized by researchers. For example, role-model theory suggests that mother's work has a positive effect on child's attainment, since by working, a mother can present a good example for her children to follow. If this is the case, the strong work disincentive of the AFDC program creates an additional difficulty in evaluating the causal relationship between a welfare program and children's attainments, since we would not know if the low achievement of welfare participants exhibited in the data is due to participation in the welfare program, or simply because of their mothers' lack of work.

Furthermore, studies on the effect of welfare participating mothers have found significant behavioral differences between short- and long-run welfare users. In addition to suggesting underlying heterogeneity in mothers' characteristics, it might also implies that welfare experience has a time-varying effect, i.e., the marginal effect of each additional year on welfare may depend on a participant's past welfare experience. This issue is closely related to the new, five-year limit on a mother's eligibility in the new TANF program. If such a nonlinear effect also exists in the case of determining a child's attainments, it is important to know whether the time limit is meaningful in terms of improvement in participating children's attainments.

To answer the above questions, this study investigates the effects of mothers' welfare and work decisions on children's attainments simultaneously. One important econometric issue is that, with the existence of unobserved characteristics, OLS estimator is inconsistent. For example, certain issues faced by a single mother (for example, parental depression due to poverty, stress from work, and marital status); though they are unobserved by econometricians, surely affect a mother's work and welfare participation decisions, as well as her children's attainments. Also, each child may have specific needs that could affect the mother's decisions during his or her childhood. Let us say a child was born less healthy than his siblings. In this case, his mother may need to take more time off from work, or may need to apply for AFDC for Medicaid coverage.[3] The child may also have a lower attainment because of this situation. If we do not take into account for these unobserved factors that simultaneously affect mothers' decisions and children's attainments, our estimates of the effects of work and welfare are very likely to be biased.

In this study, I use a random effect instrumental variables (REIV) estimator to address the

[3]Before the expansion of Medicaid in 1986, applying for AFDC was the main way for poor families to have their children covered by a health insurance program.

issue of unobserved characteristics. The rationale of this estimator is as follows: First, sibling comparisons under a random effect framework can be used to control for heterogeneity in the unobserved characteristics that are faced by siblings in a family. Then, I use an instrumental variables (IV) approach to control for remaining, more child-specific unobserved characteristics that may influence mothers' work and welfare decisions. As the REIV estimator uses more information that can be obtained from the sample to control for the effects of unobserved characteristics, it is better than using sibling comparisons or an IV approach separately, as is done by most previous studies.

An alternative way to implement sibling comparisons is by a fix effect (FE) procedure. An FE estimator is more general than an RE estimator, for it allows the unobserved characteristics to be correlated with the observed ones, while an RE estimator does not. However, the differencing procedure at work of an FE estimator has several disadvantages. First, important time-invariant characteristics of the mother (for example, an important measure of a mother's innate ability available in NLSY, her AFQT scores) will be differenced out. Second, as discussed by Currie and Thomas (1995), the differencing procedure may discard many of the true signals, while remain the noise, and hence may bias the FE estimates toward zero. Furthermore, the FE estimator imposes stronger requirements on the sample, as the effective sample includes only those children that have at least one observed sibling. Due to these reasons, I use the RE estimator in this research.

After the procedure of sibling comparisons, the remain unobserved characteristics are controlled by a standard IV approach. Since the AFDC benefit level is determined exogenously by the state government (under the guidance of the federal government), the variation in the benefit structures across states are often used as instruments.

The instrumental variables used in this study include the state benefit rule parameters. By specifying and estimating benefit rules for each U.S. state in which the sample parents reside, I can identify the different economic incentives implied by the AFDC benefit rule. These incentives - including the contribution of an additional child to the AFDC benefit, the implicit tax rate on family financial resources (other than labor income), and the implicit tax rate on the mother's labor income, can help to separate the effects of mothers' work decisions from those of the welfare decisions. In particular, a mother's work decision can be identified by the variation in the implicit tax rate on labor income, since it directly changes her reservation wage.

These economic incentives provide me more exogenous variation than previous studies on this subject have used, as they often use only a subset of these parameters. For example, the statutory benefit level for a single mother with two children and no family income (the so called “guarantee” benefit level) is widely adopted as IV by previous studies. However, guarantee level does not include the work disincentive implied by the AFDC benefit structure.

To obtain a more homogenous sample of welfare participants and non-participants, the estimation is restricted to children who were born to single mothers with twelve or fewer years of schooling. A child’s childhood is defined as his ages 1 to 5. The attainments I investigate include both short- and long-run outcomes of the child. The short-run child attainments under consideration are the Peabody Individual Achievement Test math and reading recognition scores for the Children of the National Longitudinal Survey of Youth 1979 cohort. The long-run attainments are a child’s number of years of schooling by age 25 and his or her early adulthood labor income, drawn from the Panel Study of Income Dynamics. To investigate the possible time-varying effects of a mother’s choices, I assume that the dependence of her child’s attainment on these choices follows a flexible functional form.

The REIV estimates imply that, relative to no welfare participation, participating in welfare for one to three years provides up to a five percentage point gain in the child’s PIAT test scores. The estimated positive effect of welfare on test scores disappears with four or more years of participation. The negative effect of childhood welfare participation on adult earnings found by others is not significant when one accounts for mothers’ work decisions. Hence, the message on welfare participation is mixed. On the one hand, participating in the welfare program for a short period of time – for example, no more than three years – does help to improve a child’s short-run test scores. On the other hand, it does not seem to improve children’s long-run attainments.

As for the effect of a mother’s work decision, at the estimated values of the model parameters, a mother’s work experience contributes between $3,000 and $7,000 1996 dollars to her child’s labor income, but has no significant effect on the child’s PIAT test scores. Empirical results indicate that work has no effect on short-run test scores. However, in the long run, empirical suggests that the role-model effect of mother’s work determines a child’s attainments. Finally, a child’s number of years of schooling is relatively unresponsive to his or her mother’s work and welfare participation choices.

The structure of the paper is as follows. In the next section, I provide a review of previous studies of the effects of welfare on children's attainments. In Section 3, I provide an econometric model of children's attainments, then propose a REIV estimator in Section 4. Section 5 describes the sample I am choosing. Section 6 shows the REIV estimation results, and Section 7 tests their robustness. Section 8 offers conclusions to the research.

2 Background

Most studies that relate to welfare and children's attainments focus on the determinants of children's attainments (see reviews by Haveman and Wolfe, 1995), or on the consequences of growing up in poor families (see the collection of recent studies by Duncan and Brooks-Gunn, 1997).

In both types of literature, the researches use samples of all children they can obtain in data surveys. For example, Corcoran *et al.* (1992) use all male children from the PSID survey. Using OLS estimators and almost all the information they can obtain from PSID, they find that men who are black and from low-income or more welfare-dependent families have a significant negative lower early adulthood labor income. Given the big differences between AFDC participants and non-participants' family structures and financial status, it is not surprising that researchers generally have found significantly negative relationships between welfare recipiency and children's attainments of all sorts.

Many studies, such as Currie (1998), Duncan *et al.* (2004), and Dahl and Lochner (2005), have pointed out, the negative relationships do not necessarily indicate a causal connection. Since childhood poverty is often linked with parents' stress, nutrition insufficiency, and several mental and physical health issues, these negative coefficients on welfare recipiency may capture only the disadvantages of growing up in poor families. Hence when it comes to evaluating the effect of welfare programs, it is necessary to restrict the sample to include only children who are eligible to participate in the welfare program.

However, we have little information on the causal relationship between the welfare program and a child's attainment (also see above references). Hill and O'Neill (1994) and Currie (1995) who investigate the effect of AFDC on a child's short-run test scores, Currie and Thomas (1995) and

Garces *et al.* (2002) who investigate the effect of Head Start, are among the few studies that use nationally representative samples.[4]

Among them, Hill and O'Neill (1994) and Currie (1995) adopt the instrumental variables approach to control for the effects of an individual's unobserved characteristics. Currie (1995) uses the variation in the "guarantee" benefit, i.e., the AFDC monetary benefit for a single mother with two kids and no income, to identify the effects of mother's welfare decisions, while the identification of Hill and O'Neill (1995) mainly comes from the nonlinear functional form (probabilities of work and welfare) of their instrumental variables. After applying the IV approach, both studies found that the mother's welfare experience has no effect on her child's short-run test scores. Furthermore, Hill and O'Neill find that work has a significant negative effect on test scores.

On the other hand, Currie and Thomas (1995) and Garces *et al.* (2002) use sibling comparisons to investigate the effect of Head Start. By assuming members in a family face the same unobserved characteristics, they use sibling comparisons under a fixed effect framework to identify the causal effect of a mother's decisions. Currie and Thomas (1995) find that Head Start has different effects (from insignificant to positive) on test scores based on a child's ethnic background, and Garces *et al.* (2002) find that it has a positive effect on a child's long-run outcome measures, such as crime rate.

However, Dahl and Lochner (2005) point out that neither the IV approach nor sibling comparisons can fully control the effects of unobserved characteristics, since these characteristics are very likely to be both individual- and family-related. As a result, they suggest a fixed effect instrumental variables (FEIV) estimator, which combines sibling comparisons (under fixed-effect setup) and instrumental variables approaches. Using FEIV estimates, they find that work has no significant effect on a child's short-run test scores, but they do not include welfare in their investigation.

Gottschalk *et al.* (1994) and Corcoran (1995) both point out that short- and long-run welfare mothers are different in many aspects, such as criminal behavior and inter-generational poverty correlation. Aside from the possible unobserved heterogeneity that may result in their differences,

[4] Experiment-based data, if available, can also be used to evaluate welfare program. See Duncan et al., 2004 for further discussion. In principle, random assignment enables us to derive the causal effect of welfare programs by simply comparing treatment and control groups. Studies using randomly assigned samples generally find positive effects of the welfare program. However, Currie (1998) has pointed out, if members of the control group do not accept their "fate" (and hence behave differently), the estimation may be biased upwards. Also, due to the limited scale of these experiments, there is also questions on generalization of the results.

another explanation is that welfare has time-varying effects on participant outcomes, i.e., the marginal effect of an additional year on welfare also depends on previous welfare experiences. If such time-varying effects exist, it is possible to have an average zero (or insignificant) overall effect, even though the effects of different years may be significant. In this case, the linear term of accumulating welfare experience adopted in the above studies does not fully explore the available information on the effects of welfare participation.

Based on the above discussion, the main concerns in the empirical investigation include: (i), mothers' decisions may have time-varying effects on children's attainments; (ii), using either instrumental variables or sibling comparisons may not fully control the unobserved characteristics; and (iii), as the AFDC benefit rule induces a strong work disincentive, we need to consider mothers' welfare and work decisions simultaneously. I will address these issues in the following sections. First, I propose an economic model that motivates my empirical specification of children's attainments in Section 3. In Section 4, I propose a random effect instrumental variables (REIV) approach to solving the unobserved heterogeneity problem.

3 Economic model

In this section, I use a Becker-Thomes model following the framework in Peters (1992) to describe the formation of a child's attainment. In the model, the attainment of a child i of mother j, A_{ij}, is determined by the available financial resources during the child's childhood (Y_{ij}), the child's endowment (E_{ij}), and a family environment variable (C_{ij}). A child's childhood is defined as from his ages 1 to 5 (before the child attends school).

A child's attainment formation can be expressed as:

$$A_{ij} = \beta_0 + C_{ij} + \beta_6 Y_{ij} + \beta_7 E_{ij} + \epsilon_i, \tag{1}$$

where ϵ_i in the equation captures unobserved characteristics of each child, as each child may have specific needs that could affect the mother's decisions during his or her childhoods. For example, let us say a child was born less healthy than his siblings. In this case, his mother may need to take more time off from work, or may need to apply for AFDC for Medicaid coverage.[5] The child may

[5] Before the expansion of Medicaid in 1986, applying for AFDC was the main way for poor families to have their

also have a lower attainment because of this situation.

The family environment in which the child is raised C_{ij} can be associated with a mother's decisions during her child's childhood. Since this study focuses on the effects of mothers' work and welfare decisions, I write C_{ij} as:

$$C_{ij} = \beta_1 W_{ij} + \beta_2 W_{ij}^2 + \beta_3 H_{ij} + \beta_4 H_{ij}^2 + \beta_5 X_{ij}, \tag{2}$$

where $W_{ij} = \sum_{t=1}^{5} \omega_t^{ij}$ is mother j's cumulative welfare experiences during her child i's childhood, and ω_t^{ij} is j's welfare participation decision at her child i's age t. $\omega_t^{ij} = 1$ if she decides to participate in welfare. $H_{ij} = \sum_{t=1}^{5} h_t^{ij}$, is mother j's cumulative work experiences during her child i's childhood. I assume a mother chooses only to work or not to work, and h_t^{ij} is defined accordingly.[6] Finally, X_{ij} is a child's time-invariant observed characteristics. Table 1 includes a complete list of these variables.

Also note that a mother's decisions can have time-varying effects on her child's attainments. More specifically, a child's attainment is a quadratic function of her mother's work and welfare decisions.[7] Under this setting, the total (and marginal) effect of a mother's each decision on her child's attainment is a linear combination of the parameters as well as her previous experience of the decision. A quadratic functional form is more flexible than a linear one, but it is more restrictive than a nonlinear functional form, using, for example, different dummy variables representing five different possible years of being on welfare during childhood.

The available financial resources are determined by taking the average of all the financial resources available during a single mother's child's childhood (from $t = 1, ..., 5$), including other income (Y_{ij}^O), the mother's labor earnings (Y_{ij}^L), and welfare benefit (B_{ij}). This can be written as:

$$Y_{ij} = \frac{1}{5} \sum_{t}^{5} \{Y_{ij,t}^O + h_{ij,t} Y_{ij,t}^L + \omega_{ij,t} B_{ij,t}\}, \tag{3}$$

where a mother's earnings will be determined by her work decisions ($h_{ij,t}$) in each period, the amount of time she decides to spend working, and the wage rate she is offered. To simplify

children covered by a health insurance program.

[6]In the empirical research, I've also estimated the specification in which mothers can choose to work part- or full-time, or not to work at all. The results are similar to the results of the reported specifications.

[7]A standard second-order Taylor Expansion on two variables should have included an interaction term between the two variables. In our case, the interaction implies that the effects of the welfare program also depend on the work decision. That is, two children with, among other things in common, the same number of years on welfare during their childhoods, would have different attainment levels, had their mothers worked different number of years during their childhoods. However, estimations including the work-welfare interaction term fail to pass F tests.

the matter, I assume Y_{ij}^L and B_{ij} are exogenous to the model.[8] By including labor earnings in the model, the effect from work decisions, which will be discussed momentarily, captures mainly two opposite effects, namely, time and role-model effects. The first presumably hinders a child's development because work reduces the time a mother can spend with her child. The second improves a child's attainment because mother's work presumably provides her child a good example to follow.

Assuming a child's endowments (E_{ij}) are inherited from parents following a Markov process, we have

$$E_{ij} = \gamma E_j + u_i, \tag{4}$$

where E_j is a mother's endowment level, γ measures the inheritability of cognitive ability, and u_i is a random i.i.d. noise.

Furthermore, a mother's endowment E_j can be obtained by relating to her ability formation equation A_j, where

$$E_j = \alpha_1 A_j + \alpha_2 X_j + \epsilon_j. \tag{5}$$

ϵ_j can be thought of as the mother's unobserved characteristics that are not captured by the observed variables. Certain issues faced by a single mother (for example, parental depression due to poverty, stress from work, and marital status); though they are unobserved by econometricians, surely affect a mother's work and welfare participation decisions, as well as her children's attainments.

Combining (1), (2), (3), (4), and (5), we have child's i's attainment formation as:

$$\begin{aligned} A_{ij} = \beta_0 + \beta_1 W_{ij} + \beta_2 W_{ij}^2 + \beta_3 H_{ij} + \beta_4 H_{ij}^2 + \beta_5 X_{ij} \\ + \beta_6 Y_{ij} + \gamma(\alpha_1 A_j + \alpha_2 X_j) + [\epsilon_i + \gamma\epsilon_j + u_i] \end{aligned} \tag{6}$$

.

[8] Also, by using average financial resources as opposed to accumulated ones, we might be able to reduce the effect of measurement errors, assuming it occurs in an i.i.d. random manner.

4 Econometric Issues

In this section, I show that OLS estimator of equation (6) are inconsistent, and suggest using a random effect instrumental variables (REIV) estimator instead. The estimator first employs sibling comparisons in a random effect framework to control for heterogeneity in unobserved family characteristics. An instrumental variables approach is then used to address unobserved heterogeneity in a child's characteristics that may influence his or her mother's work and welfare decisions. By specifying and estimating an AFDC benefit determination rule for each U.S. state in which sample parents reside, I take into account the variation in mothers' economic incentives that arises from differences in states' benefit structures. This variation, together with sibling comparisons, provides identification for the REIV approach.

4.1 Random Effect Instrumental Variables Model

Define a mother's decisions, $(W_{ij}, W_{ij}^2, H_{ij}, H_{ij}^2) \equiv d_{ij}$, and the effects from decision variables, $(\beta_1, \beta_2, \beta_3, \beta_4) \equiv \beta$. Let X_i be the rest of the child's observed variables. The basic econometric model is:

$$A_{ij} = \beta' d_{ij} + \pi' X_i + \epsilon_{ij}, \tag{7}$$

where $\epsilon_{ij} = \gamma\epsilon_j + \epsilon_i + u_i$. u_i is an i.i.d. random variable.

Using nationally representative data set such as the NLSY or PSID surveys, previous studies have generally estimated different versions of equation (7) by OLS models (see reviews by Haveman and Wolfe (1995), Duncan and Brooks-Gunn (1997), and Duncan and Ludwig, 2004). The primary concern is that OLS models do not consistently estimate β. The argument can be stated as follows. With the existence of both a mother's and her child's own unobserved characteristics, we have:

$$\mathrm{E}(\epsilon_{ij}|X_i, d_{ij}) = \gamma \mathrm{E}(\epsilon_j|X_i, d_{ij}) + \mathrm{E}(\epsilon_i|X_i, d_{ij}),$$

which will not be zero if either ϵ_j or ϵ_i is correlated with the mother's decisions d_{ij}. The discussion of these two terms in Section 3 gives several examples of why this might be the case. As a result, OLS estimators based upon (7) are generally inconsistent.

Furthermore, since mothers with a higher innate ability (a high ϵ_j), or with children in better condition (higher ϵ_i), may also tend to work more and be on welfare less during their children's childhoods, it is very likely that $\text{Cov}(\epsilon_{ij}, H_{ij}) > 0$ and $\text{Cov}(\epsilon_{ij}, W_{ij}) < 0$. As a result, we can infer that OLS estimator $\hat{\beta}$ is upward-biased for the effects of a mother's work decision, and downward-biased for those of a mother's welfare participation decisions.

Setting aside ϵ_i for the moment, several methods can be used to control family effect ϵ_j. Fixed- and random-effect estimators are among the most widely adopted. An FE estimator is more general than an RE estimator, for it allows ϵ_j to be correlated with X_i, while an RE estimator does not. However, the differencing procedure at work of an FE estimator has several disadvantages. First, important time-invariant characteristics of the mother (for example, the measure of a mother's innate ability, her AFQT scores) will be differenced out. Second, as discussed in Currie and Thomas (1995), the differencing procedure may discard many of the true signals, while remain the noise, and hence may bias the FE estimates toward zero. Furthermore, the FE estimator imposes stronger requirements on the sample, as the effective sample includes only those mothers with more than one child.[9] Due to these reasons, I use the RE estimator in this research.

On the other hand, the correlation between d_{ij} and ϵ_i can be controlled by a standard IV approach as long as we can find a set of instrumental variables that are correlated with a mother's decisions, d_{ij}, yet are uncorrelated with ϵ_i.

4.2 Constructing Instrumental Variables for Mothers' Decisions

This section introduces my method of constructing instrumental variables for d_{ij}. The sources of identification are discussed in the next section.

Let C represent a single mother's two-dimensional choice concerning work and AFDC participation. I assume the mother has four alternatives, with domain ({work or not}$\times$ {participating in welfare or not}). This two-dimensional choice problem can be estimated by a multinomial logit model as follows:

[9] This is an especially important concern in this research, as the average "observed" siblings is just about 1.7, although the average number of siblings in the sample is from 2.3 in the NLSY sample to 4.1 in the PSID one.

$$\Pr(C = m) = \frac{e^{\beta'_m Z}}{1 + \sum_{k=1}^{3} e^{\beta'_m Z}}, \text{ for } m\text{=1, 2, 3}$$
$$\Pr(C = 0) = \frac{1}{1 + \sum_{k=1}^{3} e^{\beta'_m Z}}$$

In the estimation, the comparison group (C=0) consists of the {No Work, No Welfare} mothers, and m =1, 2, 3 are the remaining alternatives. The explanatory variables (Z) are: (i), mothers' characteristics, including age, race, number of years of education, number of children, other income (in 1996 dollars), location indicators, lagged welfare, lagged work; and (ii), excluded explanatory variables, including four vectors of state benefit parameters.

The estimated marginal probabilities of work and AFDC participation in the child's age t are given by:

$$\widehat{\Pr}(h_t) = \widehat{\Pr}(h_t,\ \omega_t = 0) + \widehat{\Pr}(h_t,\ \omega_t = 1)$$
$$\widehat{\Pr}(\omega_t) = \widehat{\Pr}(h_t = 0,\ \omega_t) + \widehat{\Pr}(h_t = 1,\ \omega_t).$$

Then, the sums of a mother's estimated probabilities of work and AFDC participation during her child's childhood from ages 1 to 5, $\sum_{t=1}^{5} \widehat{\Pr}(h_t)$, $\sum_{t=1}^{5} \widehat{\Pr}(\omega_t)$, and the squared terms, $\{\sum_{t=1}^{5} \widehat{\Pr}(h_t)\}^2$ and $\{\sum_{t=1}^{5} \widehat{\Pr}(\omega_t)\}^2$, are used as instrumental variables for the real observations in the second stage REIV estimator of the child's attainment production function (equation (7)) .

4.3 Identification

The identification of the effects of mothers' decisions comes from the exogenous variation in mothers' economic incentives implied by the state benefit structures. These incentives, including the contribution to the AFDC benefit of an additional child, the effective tax rate on family financial resources (other than labor income), and the effective tax rate on mother's labor income is important in isolating the effect of mothers' work decisions, since it directly changes her reservation wage. I will discuss this strategy in further detail below.

Since AFDC is a state-administered program, participants' statutory benefits are exogenously determined by state governments (under the guidance of the federal government). These benefits do affect mothers' likelihoods of participating in welfare or work, and it is reasonable to assume they are uncorrelated with children's attainments. As a result, the statutory AFDC benefit levels are widely adopted to provide identification of participants' decisions (see a survey of instruments used in these studies by Moffitt, 2000).

However, the structure in determining a participant's AFDC monetary benefit level (the so-called benefit rule) is a complicated nonlinear function depending on at least family structure, size, income, and parents' work decisions. There is a wide range of candidates to choose from. For example, many previous studies choose guaranteed statutory benefits for a single mother who has two eligible children with no income, to serve for the identification purpose.

As the AFDC benefit determination structure implies different economic incentives for mothers' behaviors, it is natural to use parameters of the benefit rule, rather than particular levels of benefit, to provide identification. In this research, I assume the state annual benefit rule follows:

$$B_{is} = b_{0s} + b_{1s}N_{is} + b_{2s}N_{is}^2 + b_{3s}Y_{is}^O + b_{4s}Y_{is}^L,$$

where B_{is} is the monetary level of benefit of individual i who lives in state s. N denotes the number of children in the family. Y^O refers to a family's unearned income (not including AFDC and Food Stamps benefits, or labor income of a single mother). Y^L is a single mother's labor income. The sample includes only those mothers who have welfare receipts information (hence all of them have positive number of children).

These parameters capture different economic incentives implied by the AFDC benefit structures. In particular, b_{1s} and b_{2s} account for the marginal contribution of an additional child to the AFDC benefit. Since b_{2s} represents the fact that the contribution of an additional child to the AFDC benefit is decreasing in total number of children, $b_{2s} < 0$. b_{3s} and b_{4s} represent the effective tax on unearned and earned income, respectively. They are hence both negative as well. b_{0s} is included to capture the states' time-invariant generosities in their benefit structures.

The benefit parameters estimation for each U.S. state is done by pooling all welfare receipt information of single mothers in the PSID survey from 1968 to 1990, with state dummy variables D_k to denote the state where sample single parents reside in. Let $k = 1$, denoting the state of California, as the base state. The benefit rule for state s is:

$$B_{is} = \sum_{k=1} D_k\{b_{0k} + b_{ks}N_{ik} + b_{2k}N_{ik}^2 + b_{3k}Y_{ik}^O + b_{4k}Y_{ik}^L\} \quad \text{if } k = s \text{ and } N_{is} > 0$$

The estimated parameter vectors, $\{b_{1s}, ...b_{4s}\}_{s=2}^{K}$, where K is the total number of states for which I can estimate the benefit rules, will be used as instrumental variables in estimating the probabilities of mothers' decisions.

A detailed description of the estimation of state benefit rules appears in Appendix A.1. There are some points to make here. First, using state benefit rule parameters is more general than using the guarantee levels, since different guarantee levels are just linear combinations of b_{0s} to b_{2s}. Furthermore, using the four parameter variables separately as instrumental variables captures the different economic incentives implied by the AFDC rule, and these incentives will help us identify mothers' different decisions. On the contrary, the guarantee level does not take into account the effect of the relative wage change due to the implicit tax on labor income b_{4k}, which is apparently more relevant in identifying a mother's work decision.

Second, recent studies reveal growing concern about the existence of unobserved state factors that may simultaneously affect mothers' decisions and children's attainments. For example, a state with a more generous benefit rule is also more likely to have a better system of assisting poor families in raising their children. If this is the case, the parameters from estimating state benefit rules by the information of only that state (as do Keane and Wolpin, 2002), will be likely to suffer from the unobserved state characteristics problem. In the estimation, I assume the states' time-invariant generosities can be captured by the constant term. Thus excluding the constant terms as instrumental variables can partly solve this problem.[10]

Third, by including welfare receipts information of more than 30 years, I am using the long-run variations in the benefit rules among states to identify the effects. As real welfare benefit has continued to decrease since the 1960's (for example, mean guarantees has decreased for about 31% from 1972 to 1996. See footnote A-1 in Appendix A.1), while real family income has nearly doubled during roughly the same period, we may overestimate the effective taxes on incomes for the sample periods. However, as the main source of identification comes from variation *across* states, they can be used to identify mother's decisions as long as the estimated tax parameters do not change the *distribution* of benefit parameters across states.[11]

[10]The unobserved state characteristics are also likely to affect the slope terms. However, it is difficult to isolate them if we are going to assume that the states' slopes are not all the same.

[11]To test the sensitivity of my results, I also use the annual benefit rule parameters estimated by Fraker et al. (1985) and McKinnish et al. (1999) as instrumental variables in constructing my instrumental variables. The estimates of child's attainments are almost identical to those using my estimates. See Section 7.5 for further

5 Data and Sample

To evaluate the effects of the welfare program, I focus on children whose mothers have at most twelve years of schooling, and have been single for at least one year during their children's childhoods.[12] The reason for avoiding use of all single mothers who are financially eligible for welfare is that financial eligibility is, to some extent, the result of a mother's decisions. Focusing on the children of this group therefore creates a more serious sample selection problem.

Since most children start their schooling at age six, I define a child's childhood as his or her period of ages one to five. I separate a child's attainments into short- and long-run outcomes. The short-run attainment is the math and reading recognition percentile scores of the Picture Individual Achievement Test (PIAT) from the Children of the National Longitudinal Survey of Youth 1979 Cohort Survey (NLSY 79 Children). The longer-run attainments include a child's number of years of schooling by the age of 25, and his or her early adulthood labor income (from ages 25 to, at most, 35). Since they involve a longer time span than NLSY 79 Children can provide, I use the data from the Panel Study of Income Dynamics (PSID).

In the sample, I convert all annual monetary variables into real 1996 dollar amounts using the Personal Consumption Expenditure Deflator (PCED). Below is a brief summary of my empirical strategy for constructing both NLSY and PSID mother-child pair samples.

5.1 Short-Run Attainments: the NLSY Sample

In the NLSY 79 Children survey, a mother's profile from one year before giving birth to one year before her child starts school (age 5) is readily constructed. Each child's profile includes his mother's time-invariant characteristics, as well as her quarterly work history and detailed information on her various sources of income. A family's monthly AFDC receipts can be found in a mother's main NLSY 79 profile.

The short-run attainment I adopt focuses primarily on a child's math and reading abilities,

discussion.

[12] An alternative way to construct the sample is to require mothers to have always been single during this period. The estimation results are similar, but this requirement significantly reduces the sample size (by about 60%) and the significance of the estimation.

measured by his or her assessment scores on PIAT. Since 1986, PIAT has been assessed biannually and given repeatedly to children starting at the age of 5. I use a child's first observed test scores as his short-run attainments.[13] For the NLSY79 Children, PIAT assessments include each child's ability in math (PIAT math), in reading (PIAT reading recognition), and deriving meaning from printed words (PIAT reading comprehension). Each assessment begins with five age appropriate simple questions (also know as basal), and progresses to more advanced concepts.

For each assessment of PIAT, NLSY reports three different scores, including raw and percentile scores, and each child's standardized scores.[14] Standardized scores are widely known for their increasing cohort effect, i.e., mean standardized scores are increasing over cohorts. For example, the sample of disadvantaged children used in this research has a mean reading score of 102, which is higher than the mean score of the 1968 national sample. As a result, I use the percentile score because first, it has a mechanical connection with standardized score, and second, it is easier to interpret.[15]

Among the three assessments, PIAT reading comprehension has a slightly lower number of children with valid scores than the others, due to, among other things, the technical difficulties in recording and correcting responses from children who took the test (see p. 110, User Guide). To increase the sample size, I focus only on PIAT math and reading tests. Finally, I combined PIAT math and reading percentile scores by taking a simple average of the two.[16]

The NLSY mother-child pair sample is constructed on the basis of the following criteria: (i), the child's mother must have been single at least at some point during the child's ages one to five; (ii), the mother must have, at most, twelve years of schooling; and (iii), the child must have valid PIAT math and reading scores. In the NLSY sample, there are 10,636 person-quarters of mothers' histories and the attainments of, according to different specifications, 655 to 859 children born to

[13]Since 1994, only children under the age of 14 have been given the test. The latest cohort available for this research is the year 2000 cohort, but all the sample children had their first tests taken before 2000. Furthermore, the included NLSY child sample has a majority of the children (80%) taking these tests between the years 1990 and 1998.

[14]The last score is derived from the percentile score, based on the national norming sample in 1968, with mean 100 and a standard deviation of 15. See NLSY 79 Children and Young Adults User's Guide 2000 (User Guide).

[15]An alternative measurement is the Revised Peabody Picture Vocabulary Test (PPVT-R), which measures the hearing ability of standard American English. Children older than 3 years old are given this test. Studies (for example, Hill and O'Neill, 1994) find that a mother's work is detrimental to her child's PPVT-R percentile scores.

[16]I have also estimated the two scores separately. The results are similar, but not significant at the 10% significant level.

450 to 600 mothers, respectively. Among these children, about 36% have lived for all of their first five years in single-parent families.[17]

5.2 Long-Run Attainments: The PSID sample

The long-run attainments are a child's educational and labor market attainments, derived from the annual PSID survey. Since from 1968, PSID has kept track of individuals related to members of about 7,000 1968 core families (by, for example, marriage, blood or adoption). Because PSID has changed to a biannual survey and reduced its sample size significantly since 1997, I use only the information from 1968 to 1996.

A child's educational attainment is defined by the number of years of education that the individual has received by the age of 25. The labor market attainment is defined by averaging the individual's labor income from ages 25 to, at most, age 35. It is estimated by:

$$E[Y_i^L] = \frac{\sum_{t=1}^{T_i} Y_{it}^L}{T_i},$$

where Y_i^L is the labor income for an individual i, Y_{it}^L is the observed total labor income (converted to 1996 dollar amounts by PCED deflator) of an individual i in year t, and T_i is the total number of years we observed for an individual i.[18] Since labor income typically increases with work experiences, children who were born to older cohorts may have larger estimates. As a result, I also include T_i as an explanatory variable in children's attainment estimation.

Due to the time limitations of the data, we are using the labor income from an individual's early adulthood as an estimate of his or her labor income. Finally, since some children became non-respondents in later surveys, only those children who have education observations or positive labor incomes can be used in the children's attainment regressions.

Attrition problem may be an important concern for the PSID sample, since (i) PSID has lost more than 50 percent of its initial 1968 members by the mid 1990's, and (ii) if the attrition is systematic, it might bias the estimation results. To this end, Fitzgerald *et al* (1998) find that,

[17]Because welfare reforms have allowed states much greater flexibility in designing their own benefit rules since 1990, one may worry about the mixed effects induced by the reform. To this end, I include cohort dummies in the regression, and find no significant changes to the estimation results.

[18]This method is also adopted by Corcoran *et al.*, Solon (1992), Couch and Dunn (1997), and Bjorklund and Jantti (1997).

although attrition is concentrated among individuals who have lower socioeconomic status, lower earnings, unstable marriages, and migration histories, the selection (into attrition) is largely based on transitory components, and tend to fade away over time. They suggest that "*despite the large amount of attrition, we find no strong evidence that attrition has seriously distorted the representativeness of the PSID.*"

In the estimation, I include 1996 sampling weights to control for the possible bias that could spring from attrition.[19] In the PSID sample, I first identify single mothers using the following criteria: (i), to increase the sample size of mothers, I include mothers who have had a child of between the ages of one and five between 1968 and 1978,[20] and (ii), these mothers must have been single at some point during this period, and moreover, must always have been the head of the family during their children's ages one to seven. This is to avoid the issue of single mothers living with supportive family members. Finally, (iii), mothers must have been schooled for twelve years or less.

5.3 Sample Description

Table 1 summarizes variables used in this research. Sample means of variables are weighted to represent the national population in the year of 1996.

PIAT math and reading combined percentile test score (PIAT test score) is computed by identifying each child's first valid PIAT math and reading scores, then taking a simple average of the two scores. The mean of PIAT test scores in my sample is 41%, which is much lower than the overall scores achieved by the NLSY population (51%). This highlights the fact that children from economically disadvantaged families, which comprise my NLSY sample, have lower test scores than those from average families. Children's average age of first valid observed scores is 74 months (with median at 72 months). For long-run attainments from PSID samples, children's early adulthood labor income estimates have a mean of $14,485 (in 1996 dollars), with a median income of $13,117.

[19] For NLSY, attrition is not a serious problem. As in each round, the survey retention rate is about 99%. Also, the survey conductors re-contact all initial respondents in each round, regardless of how long they had not been responding since the last interview. Once individuals re-enter the survey, events histories since the last interview are reconstructed (Pierret, 2005).

[20] This last year (1978) is set to ensure that a child who was seven years old in 1978 was at least 25 years old in 1996.

These estimates are obtained by computing the average of a child's observed (real) labor incomes during his early adulthood years (from ages 25 to, at most, 35). In the sample, the mean number of observed adulthood years is 3.7 years.[21] The average number of years of schooling the children have received by age 25 is 11.2 years. At PSID population level, this number is 11.3 years.

Comparing the PSID and NLSY samples, the most significant difference lies in their different patterns of work and welfare participation during childhood. Mothers from the PSID sample have worked less than NLSY mothers have. Including both part- and full-time jobs, PSID mothers have worked about 60% of the time during their children's childhoods, but NLSY mothers have worked 90% of the time. This might be because (i), the expansion of the EITC program in 1990s creates a strong working incentive, especially for those who were not working before the program's growth; and (ii), most of the NLSY mothers were raising their children in the 1990s, when welfare reform in many states already put a strong emphasis on encouraging participating mothers to work.

Furthermore, PSID sample mothers have participated far less in welfare (about 18% of the time during their children's childhoods) than have mothers of the NLSY sample (at 50% of the time). The different patterns can also been seen from the ratio of mothers who have never been on welfare during this period of time. The percentages for PSID sample mothers are 59% for labor income and 46% for schooling. As for the NLSY sample, it is only 30%. Also, among the welfare participants, the NLSY sample has 48% who have spent their entire childhoods (from birth to five years old) on welfare. The ratios for PSID samples are 23% and 26% for labor income and schooling, respectively.

As for other family characteristics, PSID children tend to have more siblings than their NLSY counterparts. Since PSID sample cohorts (from 1964 to 1972) were born much earlier than NLSY cohorts (between 1985 to 1995), the difference reflects the fact that the average number of children per family is decreasing over time in the U.S. population as a whole. There are also fewer Caucasians in the PSID samples than there are in the NLSY samples.

[21] Regarding the quality of the estimates, from *Money Income in the United States 1996*, the mean earning of individuals who are aged between 25 to 34, and received twelve years of schooling or less, is about $17,000. (http://www.census.gov/hhes/www/income/income96.html). This number is only slightly higher than the mean estimate.

6 The Effects of A Mother's Decisions on Her Child's Attainments

6.1 OLS and Fixed Effect Estimates

I begin the empirical analysis by presenting OLS and fixed-effect estimates of mothers' decisions. These two approaches have been widely used in previous studies concerning determinants of children's attainments.

In the first panel of Table 2, I replicate results obtained from previous studies (for example, early adulthood labor income investigated by Corcoran *et al.*, 1992) that use OLS estimators. The samples contain children from broader backgrounds, i.e., without adding single mother and education cap requirements. All of the estimates discussed below are significant at the 1% confidence level.

Using a dummy variable of childhood welfare recipiency to capture the level effect, OLS estimations show that participating in welfare is associated with a loss of 5 percentage points on a child's PIAT test scores. Welfare is also associated with a $4,281 1996-dollar loss in early adulthood labor income, and with 4.2 fewer months of schooling by age 25. The negative associations become smaller (yet remain significant at a 1% confidence level) after using the work dummy to control for the mother's work decision. This is especially true for the welfare effect on a child's labor income, which is reduced by more than $1,200 dollars than OLS results without including work. For years of schooling, the negative association is reduced by about a month. As for short-run PIAT test scores, the negative relationship does not change (I will discuss this point in further detail later). What's more, a mother's work has a significantly positive relationship with her child's attainments.

The next panel restricts the estimation sample to those children who were born to single mothers with twelve years or less schooling. This refinement eliminates two-parents and also most of the financially stable single mofthers who are not eligible for welfare. As the control group includes only those who are eligible for welfare but do not participate, this strategy uses a comparison group of single mothers that are more similar to those who are on welfare. However, this group of sample still has the issue of the unobserved characteristics that may result in the bias of OLS estimator.

Overall, refined samples already greatly reduce the negative associations we see in the OLS regressions with general samples. For the welfare dummy regressions, the negative associations are further reduced, and become insignificant for PIAT test scores. Further controlling the mother's work decision, the negative effect on number of years of schooling also becomes insignificant. As for a child's early adulthood labor income, although the effect is much smaller in magnitude, the negative relationship still persists.

It turns out that the estimated coefficients from a mother's fixed-effect model are generally insignificant. Among them, PIAT test scores do not even pass F-test of overall significance. For the other two attainments, R^2 are much smaller than OLS models. Since the observed number of siblings from samples is only 1.7 per family, the reason might be because the differencing procedure of fixed-effect estimators leaves out important information contained in the time invariant variables of children (and mothers), and leaves too much noise (as is discussed in Section 4).

6.2 Baseline REIV Estimates

Since a mother decides whether to work or to participate in the welfare program simultaneously, I estimate the joint probabilities of mothers' work and welfare participation decisions during their children's ages one to five, using the long-run state AFDC benefit rule parameters as instrumental variables. Then the cumulative estimated probabilities of work and welfare are used as IVs in children's attainments formation functions.

The REIV estimation results are listed in Table 3. A first glance shows that only the estimated coefficients of the welfare effects of years of schooling and the work effects on labor income are significant. However, we should recall that in a quadratic function, the total (and marginal) effects of welfare are combinations of both the parameters of the attainment function as well as the mother's cumulative years of decision experience. To this end, I draw the observed and predicted total effects (using the estimated parameters) of a mother's work decisions in Figure 1. I also include the 10% confidence intervals (represented by the dotted line) of the predicted outcomes.

6.2.1 The Effects of A Mother's Work Decisions

I begin the analysis of REIV estimates by first investigating the effects of a mothers' work decisions on her child's attainments. In general, the effects of work are convex-shaped. This means that a mother's work is beneficial to her child's attainments before certain thresholds. After those points, work begins to cause detrimental effects. In particular, this convexity of work effects is significant in determining a child's early adulthood labor income. The first year of a mother's work during her child's childhood is expected to "produce" a $3,000 dollars gain in the child's labor income. When she increases her number of years of work, her child's future labor income increases until the mother has worked for four years, with the labor income gain reaching about $7,000 dollars. After four years, the marginal effect of work turns negative, but the total gain remains positive even in the case of a mother who has worked throughout her child's childhood (seven years, in this case). As for the effects of work on a child's number of years of schooling, Figure 1(b) suggests that the attainment is rather unresponsive to the variation the mother's decisions. The effects vary only from 2 to 4 months, and are not very significant.

Finally, the work effects on a child's PIAT test percentile scores are fairly insignificant. Actually, some specifications I've estimated do not even pass the 10% significance level using F-test for overall significance. The insignificant work effects on short-run attainments are also found by many other studies. For example, Dahl and Lochner (2005) find that a mother's labor force participation is not a statistically significant factor in determining a child's PIAT math and reading scores (although they focus on the general sample from NLSY 79 Children). Hill and O'Neill (1994), using a child's percentile PPVT-R score, also find similar results after they control for the mother's likelihood of working by using a two-limit Tobit model. These findings suggest that a mother's work decision during her child's childhood does not significantly affect the child's short-run test scores.

6.2.2 The Effects of A Mother's Welfare Participation Decisions

Figure 2(a) to 2(c) draw the observed and predicted total welfare effects. The observed welfare effects (represented by black boxes in the figures) are the residuals of regressing attainments on mothers' and children's characteristics. In the figure, the light-colored line shows the REIV estimates from estimations without including mothers' work decisions, which I will discuss in Section

7.2.

Several things are important to note here. First, the REIV estimates of the effects of welfare on a child's early adulthood labor income are not only insignificant (at the 5% confidence level, while the figure shows a 10% level), but also much smaller in magnitude compared to the significantly negative and sizable OLS estimates – even a child who has spent all his childhood loses less than $3,000 dollars in his early adulthood labor income (and not significant at the 10% confidence level), as opposed to the average significant $2,400 dollars loss obtained by the OLS estimator. This suggests that the negative association between welfare participation and a participating child's labor income no longer exists, after a REIV estimator is used.

For a child's number of years of schooling, welfare has a significant (but not sizable) negative effect on a child's number of years of schooling. Even the lowest estimated negative welfare effect is only at about .4 year (less than 4 months). In fact, the observed outcomes also do not show significant nor sizable negative effects. One reason to explain the rather insensitive response might be the lack of variation in the legal drop-out ages across U.S. states. The last column of Table A-2 lists these ages (in 2004) for 36 states for which I am able to estimate the state benefit rules. The average legal drop-out age was 16.4 in 2004, meaning the minimum number of years of schooling for children residing in these states should be around 11.4. This age does not vary a lot across states. Most of the states (24 out of 36) set the legal drop-out age at 16 years old, and 9 states use the age of 17. Only California, Pennsylvania, and Tennessee set the number at 18. The importance of the legal drop-out age is that it restricts students from dropping out before this age.

Finally, although not significant, the effects of welfare experience on a child's PIAT test scores are positive for the first three years on welfare. In fact, when a mother's work decisions are not included, the effects of welfare program on her child's PIAT test scores are not only much higher (the light-colored line), but also significantly positive at the 10% confidence level (shown in the first column of Table 5). As a mother's work decisions do not influence her child's PIAT test scores, the discussion below of the welfare effects on short-run outcomes uses the estimates obtained from the specification that includes only mothers' welfare decisions.

When only mothers' welfare participation decisions are considered, REIV estimates suggest that children who have participated in welfare for three years or less show a persistent average gain of five percentage points on PIAT test scores relative to those who have not. The peak occurs between two and three years experience in the welfare program, and after four years on welfare, the effects seem to have disappeared (as they are not significantly different from zero). These results are not surprising. First, the shape of the observed welfare effects in Figure 2(c) suggests that a quadratic form in welfare experiences is a good approximation to PIAT test scores. Furthermore, despite the lower mean test scores at the two ends, three or four years of cumulative welfare experiences do correlate with positive de-characterized mean scores. Hence after using a REIV estimator, not only do the total effects from participating in the welfare program become positive until a child has been on welfare for five years, but also the positive magnitudes of the effects are much larger than those obtained before controlling for unobserved heterogeneities.

7 Additional REIV Estimates

The baseline REIV estimators combine four distinctive features to identify the effect a mother's decisions on a child's attainment. First, to identify the causal effect of the welfare participation experience on a child's attainments, we have to consider his or her mother's labor force and welfare participation decisions simultaneously. This is because welfare participants are often associated with unemployment or work only enough to fulfill the minimum requirement, due to the strong work disincentive induced by the AFDC benefit structure.

Second, to consider the time-varying effects of a mother's decisions on her child's attainments, I assume his attainment is a quadratic function in his mother's work and welfare experiences. This functional form is more flexible than a linear one, which assumes that the marginal effects of an additional year of the mother's decisions are the same. In a quadratic function setup, the total (and marginal) effects depend not only on the parameters of the attainment formation function, but also the child's past experience.

Third, to control for both a mother's and her child's unobserved characteristics, I adopt a REIV estimator which uses not only sibling comparisons under a random effect framework, but also an instrumental variables approach. The rationale is, by sibling comparisons, we can control for the unobserved family's characteristics that are unchanged over siblings. On the other hand, an IV approach takes care of the (unobserved) factors that are more likely to be individual (child) specific.

Finally, in the IV approach, the identification of a mother's decisions comes from a set of mother's economic incentives implied by the AFDC benefit structure. It contains much richer information than previous studies have used. These variables include each U.S. state's effective tax rates on earned and unearned incomes and the marginal contribution of an additional child to the monetary AFDC benefit. These rules are estimated by using the states' long-run AFDC benefit receipts information from PSID.

This section examines the robustness of the baseline results: the positive welfare effect on a child's PIAT test scores and also the positive work effect on the early adulthood income, by examining the importance of each of the above characteristics of the REIV estimator.

Also, I will check the robustness by using a similarly defined instrumental variables of benefit rule parameters estimated by Fraker *et al.*, (1985) and McKinnish *et al.*, (1999). Lastly, during an earlier presentation of this research, discussants are concerned that the positive effect of the welfare program might be from the Head Start program, which targets mainly children that are in between ages three to five. I also include the REIV estimates when Head Start is included as one of the independent variables.

7.1 Linear Specification

First, I investigate the effects of mothers' decisions using a linear specification. The linearity assumption implies that the marginal effect of participating an additional year in the welfare program is the same, regardless of previous experiences. It can also be viewed as the average treatment effect (ATE) defined by a random coefficient model. The first panel in Table 4 shows the linear REIV estimates. As we can see, under a constant marginal effect assumption, welfare effects are not significant for either PIAT test scores or early adulthood labor income. This result corresponds with those insignificant findings in the previous studies focused on children's short-run attainments. It also confirms the importance of the time-varying effects of mothers' decisions.

7.2 The Effects of Welfare Without Considering Mothers' Work Decisions

The REIV estimation results using the specification without including mothers' work decisions are listed in the second panel of Table 4. The graph of the total effects calculated using the estimated parameters are drawn as the light-colored line in Figure 2. As we can see, failing to include a mother's work decisions greatly increases the negativity of the welfare effects on her child's early adulthood labor income by almost $700 dollars per year. As for the effects on a child's years of schooling, they become even more unresponsive (almost a flat line) to a mother's welfare participation decision. As for the short-run PIAT test scores, including work decisions doesn't change the postive welfare effects. This practive shows the importance of taking into account a mother's work decision when evaluating the effects of welfare on the long-run attainments.

Next, using different subsets of the identifying strategies, Table 5 and Table 6 show the estimates for PIAT test scores and early adulthood labor income, given different experiences in mothers' decisions.[22] For the purpose of comparison, the first column of each table also shows REIV estimates.

7.3 Applying only the RE or IV Approach

The advantage of using a REIV approach is its ability to control both the mother's and the child's unobserved characteristics at the same time. The RE approach uses sibling comparisons to control for unobserved family characteristics, while the IV estimator controls for the child's own unobserved characteristics by using exogenous variation in the mother's economic incentives implied by the state benefit determination rules. It is of interest to investigate the possible effects when only one source of the variation is used to estimate children's attainments.

The second and third columns of the tables show the estimates obtained by using only the IV or the RE approach. The results suggest that using either RE or IV underestimate the benefits from mothers' decisions. For example, the maximum welfare gain using the RE is three percentage points lower for PIAT test scores. The estimates for work contribution also is decrease by $4,000 dollars using RE, and by about $1,000 dollars using IV. This results seem to suggest that a lower ϵ_i or ϵ_j discussed in Section 4 is associated with longer welfare participation, less work, and lower child's outcomes.

[22] Other comparisons are available upon request.

7.4 Checking the Source of Identification

The main identification comes from the variation in the economic incentives implied by the state AFDC benefit rules. These incentives include the marginal contribution to the benefit of an additional child, and the tax rates on unearned and earned income. Of these, the last one directly changes mother's willingness to work through price effect. It is of interest to investigate the consequences of failing to include this variable.

Specification 4 shows the estimation results using the instrumental variables that exclude the tax incentives in mothers' multinomial logit estimations. As we can see, without tax incentives, welfare's effect on PIAT test scores remains fairly stable. However, the precision is reduced, since we are now using less exogenous variation in identifying the causal effects. As for the contribution of mother's work to the child's labor income, we see that, without tax incentives, not only does the magnitude of the contribution from work decrease (by more than $1,500 dollars), but also the significance lowers. This suggests that tax incentives provide the main identification for the effects of work.

7.5 Using Different Excluded Variables

Fraker *et al.* (1985) and McKinnish *et al.* (1999) estimate the annual effective guarantees and tax rates on earned and unearned incomes for the periods of 1967-1982 and 1983-1991, respectively. Their regression model can be expressed as:

$$B_i = \alpha_0 + \alpha_1 K_{2i} + \alpha_2 K_{3i} + b_3 Y_i^O + b_{4s} Y_i^L,$$

where K_{2i} and K_{3i} are dummy variables indicating a mother has two and three children, respectively.

Their setup is similar to the one I adopt (which basically follows Keane and Wolpin (2002)), except that I (and Keane and Wolpin) assume that: (i), the marginal contribution to the benefit of an additional child follows a quadratic form, and (ii), I estimate the long-run AFDC benefit rules for each state, while they estimate the annual rules.

Both studies use the AFDC Quality Control data from the U.S. Department of Human and Health Services. Since the data set provides a much more specific and detailed information than annual PSID survey does, their estimates are arguably closer to the true (effective) benefit determination rules. Also for most years, they have enough observations to estimate annual benefit rule for each U.S. state. As a result, besides the long-run variation *across* the U.S. states, their estimates also include more, short-run variations *within* each state across years. However, as argued and supported through empirical data by Keane and Wolpin (2002), under the assumption of a forward looking behavior, short-run changes in the benefit rules are generally ignored by single mothers when they are making relevant decisions. This implies that annual benefit rule parameters may contain too much noise, and thus blur the significance of the economic incentives in identifying mothers' decisions.

To see the effect of this, I use the annual estimates of effective guarantees and tax rates by both Fraker *et al.* and McKinnish *et al.* Specification 5 shows the estimation results. For the effect of welfare on PIAT test scores (Table 5), estimation using a different set of instrumental variables further improves the estimated gain in the percentile test scores by roughly one percentage point. The maximum estimated gain (now at around 6.5 as opposed to 5.4) still occurs when a child is on welfare for around two or three years in childhood. However, including more variation (by including the variation within each U.S. state) slightly reduced the overall R^2 of the regression for about 4% (from 19 to 14%). This is also an evidence that the annual benefit rules contain more noise than the long-run ones.

As for the effects of work on a child's early adulthood labor income, specification 6 in Table 6 shows using the annual rule parameters as instrumental variables also returns similar results. The difference in the estimates between using the two sets of instrumental variables are not large. The new estimates for the positive effect of work to a child's labor income are slightly lower: the maximum gain is about $200 dollars less.

7.6 Including the Head Start Program

The Head Start program provides children's developmental services in order to meet participating children's educational, health, nutritional, and psychological needs. Since most of the participating children are around 3 to 5 years old, which overlap the time period covered by this research, it is natural to ask whether including data on Head Start participation will affect the estimation results.

Children living under the federal poverty line, or in a family that receives AFDC (after 1996, TANF) are eligible for Head Start. However unlike AFDC, Head Start is not an entitlement due to its limited budget.[23] In 1994-1995, only 38% of all eligible children between 3 to 5 years old were served. As to who is more likely to be enrolled in Head Start, Hofferth (1994) indicates that among eligibles, children in two-parent families are more likely to participate in the program. Also, mother's work status does not appear to be correlated with Head Start enrollment.

Including whether a child has ever been in Head Start as one of the independent variables, specification 6 of Table 5 shows that, although still significant, the gain from participating welfare decreases by about 3 percentage points. As for a child's early adulthood labor income, specification 6 of Table 6 shows that, once head start indicator is included, although the benefits reduce significantly, the positive trend of the effect of work remains unchanged.

8 Conclusion

Economically disadvantaged families, many of them headed by single mothers, can choose to participate in various government welfare programs that were designed to improve the well-being of the family members. However, we have limited information on the causal relationship between a single mother's joint work and welfare participation decisions and her children's short- and long-run attainments.

This research estimates the causal effects of mothers' welfare and work decisions on child attainments using a random effect instrumental variables (REIV) estimator. The estimator first employs sibling comparisons in a random effect framework to control for heterogeneity in unobserved family characteristics. An instrumental variables approach is then used to address unobserved heterogeneity in child characteristics that may influence mothers' work and welfare decisions. By specifying and estimating an AFDC benefit determination rule for each U.S. state in which sample parents reside, I include variation in mothers' economic incentives that arise from the state benefit structures. This variation provides identification for the REIV approach.

The estimation sample is restricted to children who were born to single mothers having twelve or fewer years of schooling. To avoid having to deal with mothers' participating in multiple welfare

[23] See "Programs That Mitigate the Effects of Poverty on Children", Children and Poverty, Vol 7, 1997

programs, I use participation in AFDC is used as a proxy for the overall government transfer support a single mother receives. The short-run child attainments under consideration are the Peabody Individual Achievement Test math and reading recognition scores for the Children of the National Longitudinal Survey of Youth 1979 cohort. Long-run attainments are a child's number of years of schooling by age 25 and his early adulthood labor income, drawn from the Panel Study of Income Dynamics.

The REIV estimates imply that, relative to no welfare participation, participating in welfare for one to three years provides up to a five percentage point gain in the child's PIAT test scores. The estimated positive effect of welfare on test scores disappears with four or more years of participation. The negative effect of childhood welfare participation on adult earnings found by others is not significant when one accounts for mothers' work decisions. At the estimated values of the model parameters, a mother's work experience contributes between \$3,000 and \$7,000 1996 dollars to her child's labor income, but has no significant effect on the child's PIAT test scores. Finally, a child's number of years of schooling is relatively unresponsive to his or her mother's work and welfare participation choices.

9 Tables

Table 1: Summary Statistics of Variables Used in Research

Variables	Math and Reading Percentile Scores	Early Adulthood Labor Income	Child's Years of Schooling
Mean Outcome	41.33 (19.60)	14,485 (9,923)	10.98 (1.68)
Decision Variables			
Years on Welfare	2.53 (2.09)	1.23 (1.92)	1.24 (1.99)
Years of Working	2.39 (2.06)	2.78 (3.11)	2.60 (3.04)
Predicted Years on Welfare	1.77 (1.63)	1.81 (1.71)	1.88 (1.78)
Predicted Years of Working	4.52 (.43)	4.03 (2.28)	3.87 (2.26)
Never Been on Welfare	.30 (.21)	.59 (.24)	.46 (.25)
Always been on Welfare (Among Participants)	.48 (.25)	.23 (.18)	.26 (.19)
Characteristics of Child and Mother			
Years of Observed Adulthood		5.60 (3.18)	
Age (Months) Taking Test	74.18 (11.77)		
Family Income†	12,578 (36,598)	6,520 (8,668)	6,480 (8,816)
Years under Poverty	.70 (.46)	.95 (.21)	.95 (.22)
Number of Siblings	2.32 (1.19)	4.13 (2.14)	4.03 (2.16)
Race (Black/Hispanic=1)	.63 (.50)	.73 (.45)	.77 (.42)
Gender (Female=1)	.52 (.50)	.53 (.50)	.50 (1.50)
Mother's AFQT Scores	23.95 (19.29)		
Mother's Education‡	11.16 (1.31)	.35 (.48)	.36 (.48)
Mother's Age	28.53 (4.02)	28.07 (9.04)	28.50 (9.77)
Observation	905	590	902

† : measured by the average pre-AFDC, pre-Labor family income during childhoods.

‡ : PSID samples are the percentages of mothers who have had exactly twelve years of schooling.

Table 2: Children's Attainments - OLS Regression Result

Regression Model	PIAT Math and Reading Percentile Scores		Early Adulthood Labor Income		Child's Years of Schooling	
OLS regression (without single mother and education constraints)						
Welfare Dummy	-5.00***	-5.00***	-4,281***	-2,928***	-.35***	-.24***
	(.76)	(.76)	(729)	(762)	(.90)	(.10)
Work Dummy		-.004		3,170***		.28***
		(.86)		(630)		(.08)
R^2	.25	.25	.23	.23	.42	.42
Observations	3,918		2,445		3,257	
OLS regression						
Welfare Dummy	-1.20	-1.11	-3,390***	-2,395**	-.21*	-.18
	(1.57)	(1.07)	(957)	(1,029)	(.12)	(.11)
Work Dummy		1.86		3,298***		.12
		(1.62)		(882)		(.11)
R^2	.14	.15	.25	.27	.40	.40
Mother's Fixed Effect						
Welfare Dummy	-1.64	1.59	-3,094*	-2,142	-.08	-.08
	(5.03)	(5.03)	(1,863)	(1,917)	(.20)	(.20)
Work Dummy		3.00		3,331*		.03
		(2.77)		(1,749)		(.19)
R^2	.006	.004	.04	.06	.14	.14
Observations						
Children	989		590		893	
Mothers	685		372		515	
Average Children	1.4		1.7		1.7	

*** : significant at 1% significance level. **: significant at 5% significance level. *: significant at 10% significance level.

- : Standard deviations in the parentheses are heteroscedastic-robust.

Table 3: Effects of Mothers' Welfare Decisions on Children's Attainments - Account for Mothers' Work Decision

Years on Welfare	PIAT Math and Read Percentile Scores	Early Adulthood Labor Income	Child's Years of Schooling
Welfare + Work Decisions			
W	3.06	-70	-.32 *
	(3.55)	(1,282)	(.18)
W^2	-.79	-68	.05 *
	(.66)	(210)	(.03)
H	9.33	3,272 **	.33
	(11.50)	(1,680)	(.24)
H^2	-2.33	-408 *	-.05
	(2.30)	(235)	(.03)
R^2	.20	.15	.31
Observations	819	590	897

***: significant at 1% significance level. **: significant at 5% significance level. *: significant at 10% significance level.

-: Standard deviations in the parenthesis are heteroscedastic-robust.

Table 4: Effects of The Welfare Program on Participating Children's Attainments

Years on Welfare	PIAT Math and Read Percentile Scores	Early Adulthood Labor Income
Linear Specification		
Cumulative Welfare	-.96	-307
	(1.72)	(351)
Cumulative Work	-.82	537 **
	(.62)	(237)
R^2	.20	.15
Without Work Decisions		
Cumulative Welfare	4.65 *	-893
	(2.53)	(1,171)
Cumulative Welfare Squared	-.97 *	15
	(.19)	(199)
R^2	.19	.14
Observations	819	590

***: significant at 1% significance level. **: significant at 5% significance level. *: significant at 10% significance level.

-: Standard deviations in the parenthesis are heteroscedastic-robust.

Table 5: Marginal Effects of Welfare on PIAT Test Scores - Robustness Check

Years on Welfare Specification	REIV 1	RE 2	IV 3	No Tax Incentives 4	Fraker et al. and McKinnish et al. 5	Including HeadStart 6
1	3.68*	1.93**	3.49	3.52	4.37*	1.96**
	(2.19)	(.91)	(2.45)	(2.16)	(2.49)	(.92)
2	5.42*	2.72*	5.18	5.19	6.51*	2.78**
	(3.37)	(1.45)	(3.73)	(3.34)	(3.84)	(1.45)
3	5.22*	2.35	5.06	5.01	6.42	2.45
	(3.61)	(1.63)	(3.90)	(3.59)	(4.12)	(1.64)
4	3.08	.83	3.13	2.98	4.10	.98
	(3.08)	(1.59)	(3.24)	(3.07)	(3.56)	(1.60)
5	-1.01	-1.84	-.60	-.91	-.45	-1.62
	(2.59)	(1.63)	(2.99)	(2.59)	(3.20)	(1.64)
R^2	.19	.20	.19	.19	.15	.14

***: significant at 1% significance level. **: significant at 5% significance level. *: significant at 10% significance level.

-: Standard deviations in the parenthesis are heteroscedastic-robust.

Table 6: Marginal Effects of Work on Early Adulthood Labor Income - Robustness Check

Year(s) of Work Specification	REIV 1	RE 2	IV 3	No Tax Incentives 4	Fraker et al. and McKinnish et al. 5	Including Head Start 6
1	3,066**	1,018*	2,889**	2,543	3,197**	888
	(1,601)	(628)	(1,420)	(1,618)	(1,458)	(702)
2	5,255**	1,850*	4,877**	4,325	5,404**	1,615
	(2,690)	(1,059)	(2,388)	(2,726)	(2,456)	(1,188)
3	6,567**	2,494*	5,965**	5,346	6,621**	2,179
	(3,270)	(1,298)	(2,907)	(3,328)	(2,996)	(2,996)
4	7,004**	2,955**	6,152**	5,606*	6,848**	2,582*
	(3,353)	(1,354)	(2,984)	(3,435)	(3,086)	(1,534)
5	6,563**	3,225***	5,439**	5,105*	6,085**	2,823**
	(2,965)	(1,253)	(2,641)	(3,065)	(2,745)	(1,430)
6	5,245***	3,311***	3,824**	3,843*	4,333**	2,903***
	(2,208)	(1,071)	(1,956)	(2,297)	(2,043)	(1,223)
7	3,052*	3,210***	1,310	1,820	1,590	2,821***
	(1,627)	(1,031)	(1,367)	(1,565)	(1,380)	(1,138)
R^2	.14	.16	.15	.15	.15	.16

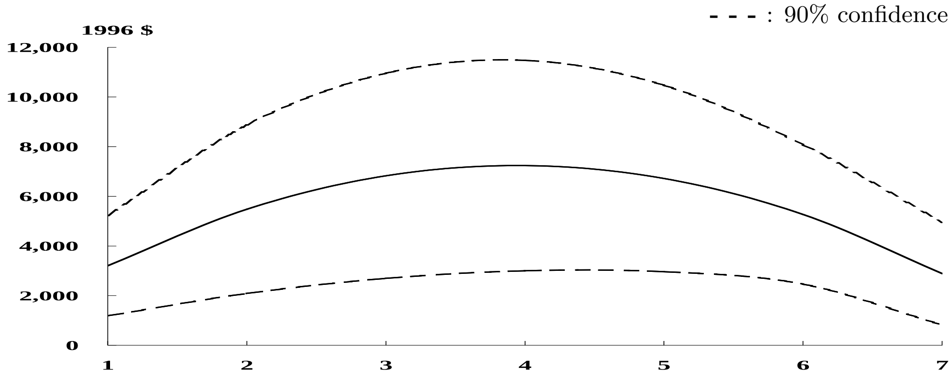
***: significant at 1% significance level. **: significant at 5% significance level. *: significant at 10% significance level.

-: Standard deviations in the parenthesis are heteroscedastic-robust.

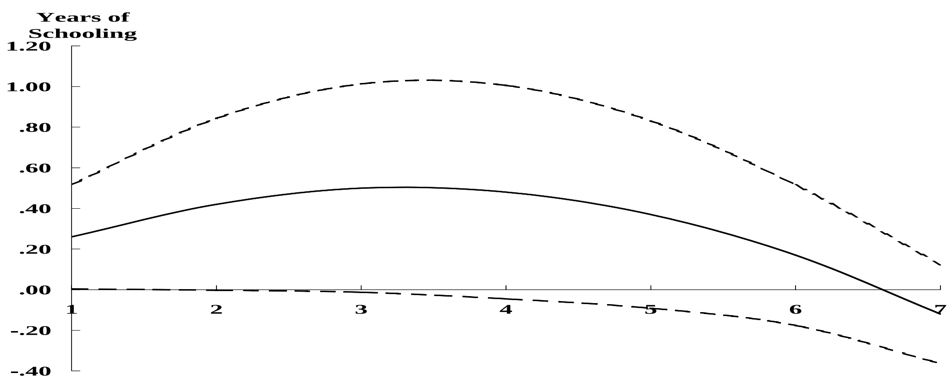
Figure 1: The Effects of Work – REIV Estimates

—— : Predicted Effects of Work Using REIV estimates

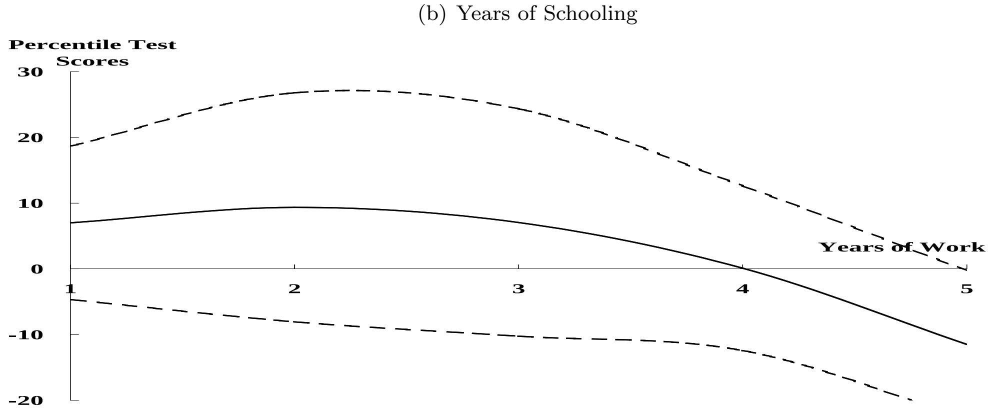
- - - : 90% confidence interval



(a) Early Adulthood Labor Income



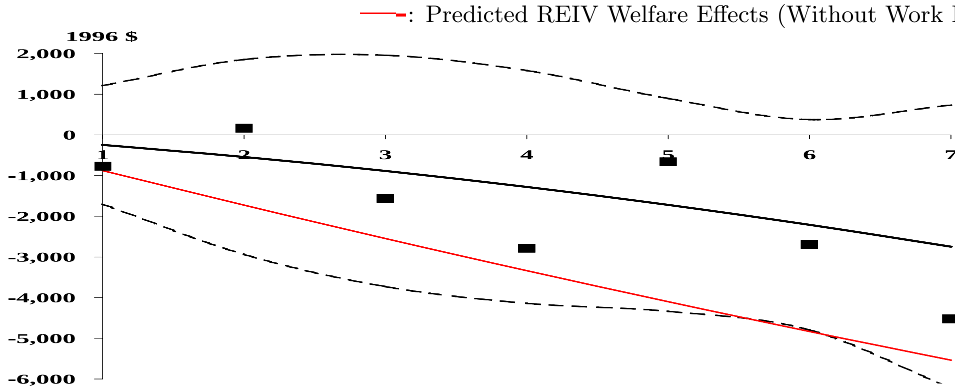
(b) Years of Schooling



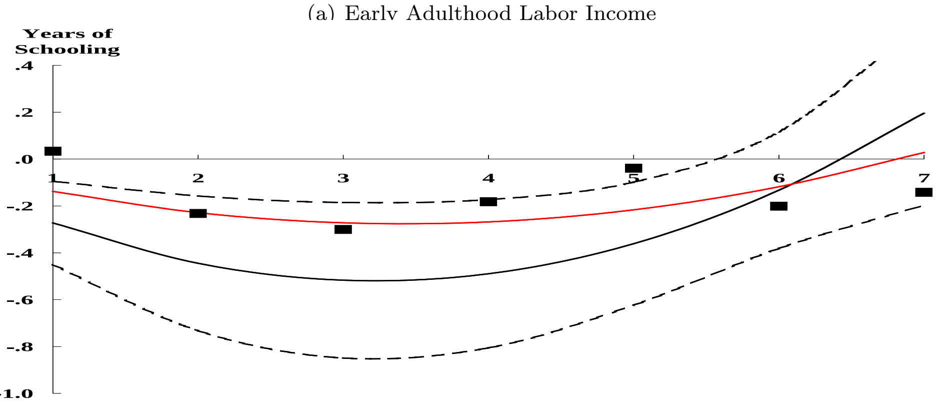
(c) PIAT Test Scores

Figure 2: The Effects of Welfare Program Participation – REIV Estimates

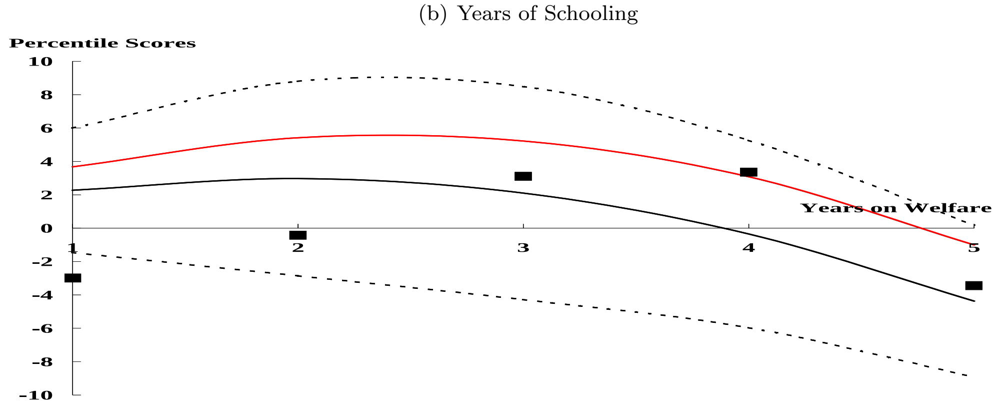
■ : Predicted Welfare Effects Using OLS regression
: Predicted Welfare Effects (REIV estimates)
- - - : 90% confidence interval
: Predicted REIV Welfare Effects (Without Work Decision)



(a) Early Adulthood Labor Income



(b) Years of Schooling



(c) PIAT Test Scores

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Appendices

A.1 State AFDC Benefit Rules Estimation Method and Results

The sample for the AFDC benefit rules estimation is formed by pooling all of the single mothers' annual AFDC receipts data in the PSID from 1967 to 1990. All the monetary variables are measured in 1996 dollars by using the state Personal Consumption Expenditure Deflator (PCED).

Also, children with unemployed parents are provided with welfare under the AFDC-Unemployed Parents (AFDC-UP) program. To avoid having to deal with the possible joint decision of the parents, I didn't include couples in my welfare benefit rule estimation. I chose 1990 as the last year because, welfare reforms have allowed states much greater flexibility in designing their own benefit rules since then.

California is used as the comparison group. In the PSID data, I did not have enough observations to estimate the benefit rules for sixteen states, including Alaska, the District of Columbia, Hawaii, Idaho, Iowa, Montana, Nevada, New Hampshire, New Mexico, North Dakota, Oklahoma, Rhode Island, South Dakota, Vermont, West Virginia, and Wyoming. As a result, the benefit rules apply only to the remaining 35 states (the last column of Table A-2 shows the number of observations in each state involved in the estimation of the AFDC benefit rules).

In general, the fitness of the benefit formula is quite good. Both R^2 and adjusted R^2 ($\bar{R}^2$) of the model are at 61% (see Table A-1), and all of the coefficients are significant at a 1% confidence level. Table A-1 lists the estimation results for the AFDC benefit rule for California. The calculation using the estimates indicate that an eligible single mother living in California with no pre-AFDC income with one child can expect to receive an annual AFDC benefit at about $\$7,529$ ($= \$5,671 + 1,922 - 64$) dollars. With an additional child, the amount of the increase in AFDC benefits would decrease by about \$33 dollars ($= 2 * (-3.09)$). Since this is not sizable, the overall increases in benefit are always positive before a mother has more than 23 kids. Furthermore, the effective tax rate on unearned income is about 8%. If she is working, the estimated effective tax rate on labor income is about 20%.

Since the guarantee benefit levels (i.e., the AFDC benefit for a single mother with two children and no income) are most often used as instruments in the welfare research, I list both the statutory and estimated guarantee benefit levels in Table A-2. The statutory benefit is deflated by using the CPI-U-X1 index, while the predicted benefit is deflated to 1996 dollars by using PCED. The table ranks both the statutory and predicted AFDC benefit levels across the included states.

We see that the statutory guarantee benefit levels do vary widely across states. The lowest level appears in Mississippi, with an average 25-year benefit worth $\$1,705$ dollars. The most generous states are California and Connecticut, at about $\$9,500$ dollars each.[A-1]

My estimation generally fits the statutory guarantee level well. In my benefit estimation, the average estimated "guarantee" ($\$5,175$) over 25 years is not far from the average of the statutory benefits ($\$5,768$), and this difference may result from using different deflators. The distribution also fits the data fairly well, especially for those states with either the most observations or the largest amounts of benefit. All states are in their correct quartiles, except for Arkansas, which is significantly underestimated.[A-2]

The estimation includes only the monetary benefits from AFDC. However, participating in AFDC is also linked with many cash or in-kind transfer programs, such as Food Stamps, Medicaid, and Housing Subsidy programs. As a result, these estimates can be viewed as the minimum benefit of participating in the AFDC program.

[A-1] AFDC benefits also show a significant decreasing trend in the real data. On the Department of Health and Human Services web site, one can find the data on this AFDC guarantee benefits level for the years 1972, 1980, 1985, 1989, 1993, 1994, and 1996. See http://aspe.hhs.gov/hsp/AFDC/baseline/5benefits.PDF. The average level of the statutory guarantee over the 35 states across these years is $\$5,768$ (in 1996 dollars), but the same guarantee over these 35 states in 1996 is only $\$4,718$; the average benefit declines by 31% in 25 years.

[A-2] I also estimate the AFDC benefit formulae by using state-by-state estimation. State-by-state estimation cannot solve the problem of state generosity. The pooling estimation performs much better than the state-by-state estimation in terms of fitness. Another concern is that the single mother may want to "chase welfare" because of the different degrees of generosity of welfare benefits across states. Using the PSID sample, I calculate children's numbers of moves during ages 3 to 7. In my sample, only 8 percent of the children have ever moved, and almost all of these children moved only once. Exactly half of the children who have ever moved are from the group of children who have ever been on welfare.

A.2 Mothers' Working and Welfare Participation Decisions

Mothers' work and AFDC participation decisions are estimated jointly using a multinomial logit model.[A-3] Since the NLSY survey provides quarterly information concerning mothers' working histories, while the PSID survey has only annual information, I separate the two samples and estimate the quarterly and annual mothers' decisions for the NLSY sample and the PSID sample, respectively. Here I report only the estimated Relative Risk Ratio (RRR) for the NLSY sample in Table A-3.[A-4] The group of mothers not working and not on welfare is set as the base category.

If the RRR of an explanatory variable for a choice is statistically greater than one, the choice would have a higher chance of being selected than the (no welfare, not work) group, given an increase in that explanatory variable.

One of the necessary conditions of valid instruments is that they be correlated with the included explanatory variables. The set of instrumental variables and the state benefit rule parameters, all exhibit a significant correlation with the mother's decisions during her offspring's childhood. Hence, our set of variables passes the first requirement of instrumental variables.[A-5]

The state benefit rule parameters include those on the number of children, number of children squared, tax rate on family's pre-AFDC, food stamp, and pre-labor income, and tax rate on labor income. The first two parameters concerning how many children a single mother has, although significant, does not seem to have sizable effects on mothers' decisions concerning work and AFDC participation (RRR are all closed to unity). The tax rates on family's other income and labor income appear to have significant and very sizable effects on mothers' decisions. Since tax rate is negatively recorded in the data, the marginal effect actually indicates a mother's reaction due to a decrease in the tax rates. In the sample, when the tax rate on family income decreases, the mother is more likely to be on welfare (as seen by the significant and sizable RRR of both the (in welfare, not work) and the (in welfare, work) alternatives shows). Compared with the (no welfare,

[A-3] To use a multinomial logit model, we need to assume the scores of the likelihood function of each year are independent.

[A-4] RRR is defined as:

$$\frac{\Pr(c=j|x=x+1)/\Pr(c=0|x=x+1)}{\Pr(c=j|x)/\Pr(c=0|x)}.$$

The estimation results are quite similar in both samples. PSID results are available upon request.

[A-5] The other condition is that the instruments should be uncorrelated with the residuals of the outcome variable. The instruments I adopt also satisfy this requirement. Estimation result available upon request.

not work) group, she is also more likely to be in the (no welfare, work) group.

In the case of the mother's demographics, when a mother's age increases, she becomes slightly (3%) more likely to be in the (work, no welfare) group compared to women in the base group. Second, mothers of different races do not appear to make significantly different choices. When a mother's education level increases, she is 22% less likely to be on welfare and to work. However, there are no significant differences in the other two alternatives and the base group among women of the same education level.

When a mother has other income, we know she is more likely to be either working or on welfare, since the RRR of all three groups is significantly higher than that of the base group. Also, the location indicators (with the South being the base group) show that single mothers in different regions seem to make different choices. For example, single mothers living in the West and Midwest regions are 2.21 and 1.65 times more likely to be in the (welfare, not work) group, respectively, while the Northeastern single mothers seem 40% less likely to be working. The lagged welfare and work decisions, just as we expect, are also strong predictors of mothers' decisions.

The next set of explanatory variables includes a series of dummy Variables. These, in turn, include whether a mother has free care support (from either the government or relatives) and whether the mother needs child care (as defined by her answers to the child care arrangement questions). The RRR of these dummy variables indicates that when a mother has free care, she is much more likely to work in the first year. However, she becomes less likely to work in the second year. In the third year, free care does not affect the mother's decisions. Furthermore, if the mother needs child care (regardless of who the provider is) in the first year, she is much less likely to work. However, after the first year, she tends to work more if she needs child care.

Table A-1: AFDC Benefit Rule Estimation Results: California (in 1996 dollars)

Coefficients	Estimation Results (S.D.)
Constant Term	5,671*** (110)
Number of Children	1,922*** (50)
Number of Children Squared	-33*** (5)
Other Income	-.08*** (.004)
Labor Income	-.20*** (.006)
Observation	10,284
R^2	.61
$\bar{R}^2$	.61

***: Significant at 1% level.

Table A-2: Statutory and Estimated Annual Guarantees for A Single Mother with two Children and No Income (in 1996 dollars)

Rank by Avg. Statutory Benefit*	Rank by Predicted Benefit	State	Average Statutory Benefit**	Predicted Benefit	Legal Dropout Age†	Number of Observations
1	1	Mississippi	1,705	1,791	17	5,161
2	2	Alabama	2,370	2,261	17	1,163
3	6	Tennessee	2,763	3,036	18	603
4	4	Texas	2,791	2,586	17	1,926
5	3	South Carolina	2,903	2,538	17	2,829
6	8	Louisiana	3,128	3,072	16	1,791
7	10	Georgia	3,780	3,535	16	1,732
8	5	Kentucky	3,829	2,418	16	630
9	13	North Carolina	4,217	3,876	16	1,061
10	11	Florida	4,226	3,585	16	2,698
11	12	Missouri	4,375	3,762	16	3,531
12	9	Arizona	4,583	3,998	16	545
13	14	Indiana	4,669	4,107	17	1,454
14	17	Ohio	5,157	4,962	16	3,644
15	22	Delaware	5,378	5,604	17	1,183
16	21	Maryland	5,580	5,594	16	4,872
17	15	Colorado	5,661	4,066	16	278
18	20	**Average Level**	5,768	5,301	16.4	69,364
19	18	Virginia	5,768	4,919	16	910
20	29	Illinois	5,878	7,203	16	4,949
21	16	Nebraska	5,923	5,063	16	255
22	26	Maine	6,233	6,838	NA	52
23	25	Utah	6,608	6,857	17	106
24	28	Pennsylvania	6,704	7,165	18	2,972
25	23	New Jersey	6,970	5,888	16	1,080
26	24	Kansas	7,048	8,129	16	494
27	19	Oregon	7,452	5,508	16	360
28	7	Arkansas	7,518	2,957	16	724
29	27	Michigan	7,572	7,302	16	8,143
30	31	Massachusetts	8,111	7,739	16	460
31	34	Washington	8,367	6,887	16	296
32	33	Minnesota	8,385	8,426	16	473
33	35	Wisconsin	8,509	9,101	17	156
34	36	New York	8,758	9,374	17	2,351
35	32	California	9,428	7,926	18	10,284
36	30	Connecticut	9,519	7,467	16	198

* "Statutory benefits" are the average statutory benefits from 1970 to 1996 adjusted by the CPI-U-X1 index. Benefit data are from Table 5.13 of "Aid to Families with Dependent Children: The Baseline." (Office of the Assistant Secretary for Planning and Evaluation, Office of Human Services Policy.)

** Predicted Guarantee includes AFDC and Food Stamp benefits.

† Online search using google.com.

Table A-3: RRR of Multinomial Logit Estimation Results: Mothers' Decisions

	No Welfare	In Welfare	
Coefficient	Work	No Work	Work
Benefit Parameters			
Number of Children	1.01***	1.00	1.01***
	(.002)	(.003)	(.003)
Children Squared	1.02	1.00	1.03**
	(.013)	(.017)	(.019)
Other Income	21.8***	12.9**	5.11***
	(34.8)	(27.7)	(.904)
Labor Income	82.3***	62.0**	10.7***
	(11.7)	(11.6)	(16.7)
Background Characteristics			
Age	1.03**	.97	1.00
	(.016)	(.021)	(.017)
Race	1.00	1.00	1.00
	(.001)	(.000)	(.000)
Years of Education	.95	.90	.78**
	(.101)	(.134)	(.093)
Number of Children	1.14**	.95	1.12*
	(.063)	(.070)	(.070)
Other Income	1.25**	1.75***	1.73***
	(.127)	(.210)	(.186)
Lagged Welfare	.26***	10.83***	20.19***
	(.744)	(3.579)	(5.976)
Lagged Work	3.30***	1.89***	25.88***
	(6.268)	(.498)	(5.731)
Location Variables			
West	.97	2.21**	.89
	(.264)	(.779)	(.265)
Northeast	.61*	1.35	.59*
	(.174)	(.503)	(.183)
Midwest	.72	1.65***	.86
	(.162)	(.487)	(.213)
Dummy Variables			
Before Birth	.18***	1.01	.45**
	(.054)	(.462)	(.168)
Around Birth	.99	.99	.98
	(.014)	(.019)	(.016)
Free Care 1st Year	1.99***	1.78*	2.14***
	(.470)	(.597)	(.566)
2nd Year	.53***	.73	.55**
	(.134)	(.259)	(.155)
3rd Year	1.12	.70	1.00
	(.267)	(.234)	(.260)
Needed Care 1st Year	.66*	.89	.60**
	(.147)	(.279)	(.149)
2nd Year	1.52*	.97	1.02
	(.376)	(.318)	(.277)
3rd Year	1.74***	1.41	1.57**
	(.369)	(.398)	(.367)
No of Person-Years	10,636		
Log-likelihood:	-4,444.18		
Pseudo-R^2	.47		

*** significant at 1% significance level.
** significant at 5% significance level.
* significant at 10% significance level.