Welfare reform and labor participation:

Are there Urban and Rural Differences?

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Abstract

Although welfare reform began in 1996 at the national level, Iowa was one of the earliest states to obtain a waiver to initiate the Iowa Family Investment Program (FIP) in 1993. To gain a better understanding of welfare recidivism, we use Iowa administrative quarterly data between October1993 and September 1995, impute the education attainment for the caseheads with missing education attainment using fractional imputation and study the factors that affect the probability of working, the potential wage for the caseheads and the possibility of leaving FIP based on the potential wage. We find higher education (i.e. higher skills) leads to higher labor force participation, especially for single-mothers with children. Metro or urban location is associated with the probability of working and potential wage earnings, but has no effect on FIP participation. The local unemployment rate does not affect labor participation of low-income individuals, but does affect the potential wage and FIP status. Those with lower education, and nonwhites are more affected by the local labor market environment than others. If an individual moves once in a year, he or she will earn more money than in the original job; no gains are achieved through moving more than once. The possibility of leaving FIP is relatively high if there is only one move.

Introduction

Although federal welfare reform legislation (the Personal Responsibility and Work Opportunity Reconciliation Act---PRWORA) was passed in August 1996, forty-three states experimented with welfare reform under waivers from Aid to Families with Dependent Children (AFDC) and Food Stamp Program rules between 1993 and 1996. Iowa was one of these earliest welfare reform states. On October 1, 1993, Iowa implemented the Family Investment Program (FIP) and a slightly revised Food Stamp Program (FSP) in 90 of the 99 counties in the state. In the remaining nine counties both pre-reform and reform programs operated concurrently. Iowa joined Oregon as one of the first two states to launch major changes in its social assistance programs (Prindle et al., 1999). The goals of FIP were to help the recipients experience significant financial benefits from employment; to move toward self-sufficiency while discouraging behavior that increases dependence (that is, shift responsibility for the long-term well-being of low-income families from the state to the parents in those families); and to foster the formation and maintenance of two-parent families (Gordon and Martin, 1999).

In 1995, Iowa launched a project to develop Iowa's administrative data system in order to evaluate the effects of FIP and other social assistance reforms. Because of greater attention on program participation and usage, there has been increased interest in the use of administrative data for social science research. Two recent evaluations note the strengths of administrative databases: the data are relatively inexpensive, and the databases are generally longitudinal and can be linked with other administrative data sets to create a comprehensive representation of program use and client outcomes (Hotz, et al., 1998 and UC DATA,1999).

We use Iowa administrative data to analyze the relationship between FIP and employment. These data were linked for all FIP recipients in April 1993. The data set includes detailed information on child support collections, FIP participation, quarterly wage earnings, household variables, and demographic variables. Because the administrative records did not require reporting on education when the individuals applied for FIP, about fifty percent of the observations have missing data on education. However, education is a major indicator of personal skills. Without the education information, it is very difficult to understand the relationship between welfare reform and employment.

There are several ways to deal with the missing data problem. Little and Rubin (1987) discuss several traditional approaches for incomplete data analysis that include using only complete cases, using available cases and imputing missing values. Rubin (1987) advocates the use of multiple imputations, the method used by Keng, Garasky and Jensen (2000). We used fractional imputation as described in Kim (2000) to compensate for missing education attainment (see Pan, Fuller and Jensen 2001 for more details).

Our study examines factors that affect the possibility of working and factors that affect the potential wage for FIP recipients in order to better understand program and labor force participation among low-income households, including differences in rural and non-rural location. In the next section, we discuss the data and outline the distribution of education variable available in the data set. Section three describes briefly the procedure of fractional imputation and jackknife variance estimation. The demographic characteristics of the household heads are given in part four. In section five, we discuss the estimation procedures; we present the numerical results in section six. The final section includes a brief conclusion.

Data

The FIP data is structured as a two-year quarterly panel, beginning with October 1993, the start of the FIP program, and ending in September 1995 (Keng, Garasky and Jensen, 2000). Most data are from the linked administrative record data for cases active in April 1993. Additional variables provide information on the economic and social conditions in the local geographic area. These variables are the poverty population as a fraction of the total population in the county and the working age population (age between 18 and 64) as a fraction of the total population. The total number of observations used in the empirical analysis is 32,783.

According to Butler and Beale (1994), Iowa can be classified into 10 metropolitan counties (Beale codes 0-3), 9 urban nonmetro (large city urban) counties (Beale codes 4 and 5), 35 “rural” adjacent counties (adjacent to a metro area, rural and small-city urban counties, Beale codes 6 and 8) and 45 “rural” nonadjacent counties (non-adjacent small-city urban and rural counties, Beale codes 7 and 9) in Iowa. Metropolitan counties are referred to as the “metro” area. The “urban” areas are urban nonmetro counties that have a city with at least 20,000 in population. The “rural” area includes small cities (less than 20,000 in population), rural adjacent and rural non-adjacent counties. In some of the analysis, we combine the metro and urban areas and refer to them as “non-rural”.

There are 23 different patterns of reported educational attainment across the eight quarters. Of the 32,783 cases, 16,010 (48.8% of the total) cases have education attainment information in all eight quarters; 14,674 observations do not have any education information. These two groups account for 93.60% of the sample. Another 2099 (6.40%) cases provided education attainment in some quarters. The imputation base is chosen from the 16,010 complete-data observations. For example, there are 110 observations without education information in the first year but with at least a high school degree in the second year. The number of individuals from the complete-data set with at least a high school degree in the second year is 10,652 observations. Therefore, these 10,652 observations are chosen as the imputation base for the pattern observed for the 110 observations with no education information in the first year.

The report rate for education attainment is between 52.89% and 54.48% in the total cases for the eight quarters. Cases reporting at least a high school degree increased from 31.21% to 35.20% of the total sample. For the 16,010 cases with complete-data, the share with at least a high school degree increased from 63.90% to 66.98%.

Of the complete cases (n=16,010), 63.90% (10,230) had at least a high school degree in October 1993, the beginning of the period, and 33.02% (5,286) cases did not have a high school degree at the end of the two years. Thus, 96.92% of the individuals did not change education category during the two-year period. There are twice as many individuals with a high school degree as those without one in the group that did not change. A total of 363 (2.27%) and 131 (0.82%) cases attained a high school degree in the first and second year, respectively.

Fractional imputation and jackknife variance estimation

To impute the education attainment, we use the fractional imputation method described in Kim (2000). We assume that educational attainment is related to gender, race, marital status, an indicator for a metro county, the number of children in the household, quarterly wage income, marital status, total number of months on FIP, the amount of child support received, the county unemployment rate and county income per capita. For some variables, such as marital status, quarterly wage income, etc., the value varies by quarter. We calculated the different parameters using the appropriate quarter's value.

We calculated the predicted values based on the models for both respondents and non-respondents. We use the model based on quarter 1 data to compute the probability of a high school degree for patterns with missing data in quarter 1; the model based on quarter 2 to compute the probability of high school degree for additional missing data in quarter 2, etc.

The respondents were ordered on the probability of education attainment in a specific quarter computed from the estimated model. Then the respondents were divided into groups of size 10. We call these groups "cells". The boundary between the groups is the probability value mid-way between the largest probability value in one group and the smallest probability value in the next group.

The non-respondents are assigned to cells on the basis of the model estimated probability values. Every non-respondent with a probability value that falls within the boundary of a cell is assigned to that cell. A set of the 10 respondent education attainments is given ("donated") to each non-respondent in the cell. The education attainment is imputed for each of the quarters for which data are missing. Each of the ten imputed vectors is given a weight equal to the original weight divided by ten. Given that one is the original weight in this data set, we assign 0.1 as the weight for the imputed data. By using fractional imputation, the educational values imputed for the non-respondents contain the actual education of the respondents in the cell. The method has the benefits of multiple imputation as well as smaller variation than the Rubin method.

The sample number of observations for each quarter with at least a high school degree after imputation for the whole data is

$$Y = \sum_{i=1}^{n} \sum_{j \in \vartheta_j} y_{ij}^* w_{ij} \ , \tag{1}$$

where

ϑ_i is the set of donors for individual i. If i is a respondent then $\vartheta_i = i$; if i is a non-respondents then ϑ_i contains ten donors;

w_{ij} is the imputed weight of donor j for individual i. If i is a nonrespondent, then there are ten donors and w_{ij} =0.1 for each of the j; if i is a respondent, then w_{ii} =1;

y_{ij}^* is the imputed value from donor j to recipient i. If i is a respondent then $y_{ij}^* = y_{ii}^* = y_i^*$ is the original observation;

n is the total number of individuals in the sample which equals to 32,783 for the total sample.

The imputed sample mean of education attainment is

$$\hat{\bar{y}} = \frac{Y}{\sum_{i=1}^{n} w_i} = \left(\sum_{i=1}^{n} \sum_{j \in \vartheta_i} w_{ij} \right)^{-1} y_{ij}^* \tag{2}$$

The variances of the survey statistics are calculated using jackknife variance estimation based on replicate weights (Westat, 1998). We treat the whole data set as a simple random sample. The jackknife variance estimator of a statistic *H* is

$$\hat{\mathrm{var}}(H) = \frac{G-1}{G}\sum_k (H(k)-H)(H(k)-H)'. \qquad (3)$$

Where *G* is the number of replicate weights. *G*=100 in our case (see Pan, Fuller and Jensen, 2000 for details) and *H(k)* is the *k*-th replicate estimate of *H*, *k*=1,2,…,G.

Descriptive analysis and results from the imputation

Table 1 gives the mean and standard error of education for quarters 1 and 8 for our imputed data set. The mean and variance are calculated by the equations (2) and (3), respectively. From the Table, one can see that the estimated share with education of at least a high school degree is 62.14% in October 1993 (Q1) and 65.12% inSeptember 1995 (Q8). Compared to data for the complete data set, there are 1.76 percentage points more in the first quarter and 1.86 percentage points fewer with at least a high school degree in the last quarter. There are 3.08% for the complete data set and 2.98% for the whole data set (including imputed education achievement) who earned at least a high school degree at some time in the two-year period.

The full data set including imputed values was used for the subsequent analysis and estimation. As shown in Table 1, for all cases (n=32,783), 62.14% of case heads have high school education (the high-skilled group) in the first quarter and 65.12% of case heads with high school education at the end of the two-year period. Following Hoynes (1999) definition, low-skilled workers are defined as case heads without a high school degree and high-skilled workers defined as case heads with at least a high school degree. The higher skilled group (those with high school education) has almost 6 percent larger share of whites; the higher skilled group also has a 1.58% larger share of disabled. In addition, the higher skilled group has more married cases, and more cases with one or two children.

In total, 53.06% of the cases were in metro areas and 41.95% were in urban areas in October 1993. The quarterly wage income and child support are two major income resources for the cases in the data in addition to FIP. There were 51.11% cases that received child support in quarter 1 (100%-46.89%) and 49.41% received the support in quarter 8. The average amount of quarterly child support received was 344.17 ($) in the first year and 622.40 ($) for the second year.

Although most of cases did not earn very high wage income in the whole sample, the share of cases without wage income fell from 45.13% in the first quarter to 30.49% in the last quarter. The share with both child support and wage income in the two years was 36.61% and 37.15%, respectively. The share without wage income is related to the unemployment rate in the county. For example, in each year, during the second quarter (January to March) the unemployment rate is the highest and the ratio without wage income in that quarter is also the highest.

The average time cases stayed in the FIP and Food Stamp Program during the two-year period observed was about 17 months. Nearly 45% of FIP cases and 42% of food stamp cases left the programs some time during the two-year period. The less skilled group stayed in a little more than did the high-skilled group.

Table 2 gives more detailed information about the cases with children. The table shows the working participation rates for the low-skilled and high-skilled cases with children. There exist significant differences between the two skilled groups for the single-females. Cases in the high skilled group have higher labor force participation rates. Although the differences between the high-skilled and low-skilled for the married groups are small, there are differences between single-mothers and married-mothers. Married females have higher working participation rates than do single females. The differences in labor participation rate for men in the four groups are not statistically different from each other. The participation rates for the females are higher than those for males except for the single low-skilled group.

Estimation procedure

We analyze the potential for exit to gain a better understanding of welfare recidivism. *An exit* is said to occur for the quarter when a FIP recipient leaves (or is out of) the program for two months in a specific quarter. We hypothesize that the odds of a recipient exiting the FIP depends on county variables such as local income per capita, local unemployment rate, local poverty level, and individual variables such as education attainment, whether they move during the one-year period, gender, disability, marriage status, number of children, and "potential" wage one can earn, etc. The potential wage one can earn is measured by the predicted maximum wage (max-wage). We choose the max-wage as a measure of labor market opportunities because labor force and FIP participation are jointly determined.

The max-wage is computed for the year using the quarterly wages for the individual. The quarter in which max-wage occurs is called *the max-wage quarter*. For example, if one individual has quarterly wages during quarters in the two-years of 1000, 2000, 3050, 1050, 3000, 4050, 5050, 6010($), the maximum wage in the first year and the second year is 3050($) and 6010($), respectively. For those who did not work when we collected the data, we chose quarter three (April-June) as a representative quarter because this quarter is the one where most of the max-wage cases occurred (40.11% in quarter three and 36.03% in quarter four). The max-quarter indicator is used to choose the independent and dependent variables for the models.

Because 10,204 individuals (31.1% in the sample) had no wage income in at least one year, the selection bias problem on labor market participation may occur when we use the data set composed of working individuals to predict the maximum wage of people not working. Least squares regression will produce inconsistent estimates of the coefficient β. Therefore, we need to make some adjustment in the model. According to Greene

(2000, page 927-932), we can view the problem as that of an omitted variable. The least squares regression of **Y** on **X** and a self-selection bias variable would produce consistent estimates if we can put self-selection bias in the model.

We proceed to estimate in three stages. First, a logistic model applied to the data yields the probability of labor participation and self-selection bias (inverse Mill's ratio); second, an ordinary least squares applied to the max-wage data yields estimates of the potential wage. Because the max-wage cannot be less than zero, the model is essentially a Tobit model (Deaton and Irish,1984) ; third, a logistic model is used to predict the probability of FIP participation.

Assume the probability of working is related to location, county unemployment rate, county labor force, gender, race, marriage, education, number of children, child support and active month in the FIP for the last half year. We use the logistic model based on replicate weights to predict the probability-of-working and use the iterative method of Newton-Raphson to solve the parameter vector *H*. Convergence is obtained when the difference in –2log-likelihood between successive steps is less than 0.025. The weighted estimate of the log-likelihood is given by

$$\sum_{i=1}^{n} W_i Z_i \log \hat{P}_i + \sum_{i=1}^{n} W_i (1 - Z_i) \log(1 - \hat{P}_i). \tag{4}$$

Where

W_i is the n $\times$n diagonal matrix of *i*-th replicate weights;

Z denotes the vector of observed individual values for working and Z_i is either 0 or 1 for each observation, $Z' = (z_1, z_2, \ldots, z_n)$;

$\hat{p}$ is the associated vector of estimated probabilities for choosing to work

$\hat{P} = (\hat{P}_1, \hat{P}_2, ..., \hat{P}_3)$ and $P = \dfrac{1}{1+e^{-\gamma H}} + u$,u is the n×1 column vector of random errors. γ is the vector of independent variables and *H* is the corresponding parameter vector.

We assume that the max-wage is related to county variables such as county income per capita, county education level, county employment rate, county labor force, county poverty level, location and individual variables such as age, race, disable, gender, number of children, education level, marriage, child support received and the time they stayed in the FIP. Let p be the number of independent variables, equal to 28 in the max-wage decision case. The max-wage equation can be written as

$$Y = \beta' X + \beta_\lambda \lambda_i + \varepsilon \,, \tag{5}$$

where

Y is n×1 column vector of max-wage income, $Y' = (y_1, y_2, \ldots, y_n)$;

β is the (p+1) ×1 parameter vector, $\beta' = (\beta_0, \beta_1, \ldots, \beta_p)$;

β_λ is the parameter for selection-bias or inverse Mill's ratio vector λ (See Green, 2000, pp. 927-932 for details);

X is the n×(p+1) matrix of independent variables, $X' = (1, x_1, x_2, \ldots, x_p)$;

and ε is the n×1 column vector of random errors, $\varepsilon' = (\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_n)$.

Note the estimate of the potential wage implied by the model may be negative, but observed earnings are not. Thus, the predicted max-wages are:

$$\hat{Y} = \max\{0, E(y_i \mid z_i = 1)\} \tag{6}$$

The caseload's FIP status in the quarter after they achieve the max-wage at time *t* is defined as

$$P_{(t+1)} = \begin{cases} 1 & if\ \ household\ leaves\ FIP \\ 0 & otherwise \end{cases} \qquad (7)$$

We use the predicted max-wage as an independent variable instead of actual wage value to estimate the FIP exiting status, because FIP status and max wage are endogenous. Assume the probability of exiting the FIP is related to location, quarterly unemployment rate, age, being disabled, marriage, potential wage at the max-wage quarter *t*, moving times, number of children, and child support received, and other factors. Then we use a logistic model to estimate the probability of being off of FIP program at *t*+1.

Empirical results

The estimated coefficients of the probability-of-working, potential-wage and being off of FIP in the next quarter are reported in Table 3.

Probability-of-labor-participation

We include several county variables in the models. Results show that the greater the share of local poverty population in the total population, the less likely the case head was to be working. The location is statistically significant at 10% level. The positive sign indicates that people living in the non-rural areas (i.e., metro and urban areas) are more likely to be working than those living in rural areas. The unemployment rate in the county is not statistically significant for the probability of working. However, the ratio of working age people in the county to total population is significant at the 10% level in the non-rural area. The negative sign suggests that the higher the ratio (the relative availability of labor) is, the less likely the FIP recipients are to be working. The results may be related to labor supply. If one county has a lower share of working age population, it has a relatively smaller labor supply and FIP recipients can more easily get a job. The net effect of location, conditioned on labor supply, is negative for non-rural areas.

Gender and race were evaluated for the four combinations (gender $\times$ race). The results show that those who are female and those who are white are most likely to work; the probability of working for male-whites, male-nonwhites, and female-nonwhites are almost the same; also, the gender indicator is not statistically significant. The reason for these results may be due to the fact that there are 90.74% female in the data. For those who are disabled, it is more difficult (and not required) to get a job. Our results consistently show that the probability-of-working for disabled persons is lower than for the abled.

Being married and having a larger number of children in the family increase the probability of working. Families with a larger number of children have more pressure to earn money so that they can support their families. However, the probability of working will decrease if the caseloads have child(ren) less than 6 years old. The results are related with the issue of child-care. If a family has a child less than 6 year old, the cost of child-care may be higher than they can earn.

The amount of child support received has a positive effect on the probability of working up to a point, and then is associated with decreased probability. To explore the situation further, we include an interaction term between education and child support received. The negative sign implies that at higher levels of child support, the turning point for the decrease in the effect of child support (from the quadratic term) occurs at a smaller level of child support for the high skilled cases than for the low skilled cases. From our results, the peak in probability of working for the low-skilled group occurs at 336.61($) per quarter child support received while the number for the high skilled group is 253.53($) per quarter. These values mean that the probability-of-working for high-skilled cases is more “sensitive” to child support than for the lower-skilled cases.

For a long time, economists have considered education as a major factor of finding a job. Not surprisingly, the results show that the probabilities of working for low-skilled cases are lower than those for the high-skilled cases. In addition, we expect FIP recipients to move and change location to find a job. The positive sign for the number of moves (between counties) in the equation indeed shows that it is the case.

Potential wage prediction

We include several county variables in the model for predicted wage. The unemployment rate in the county is negative and statistically significant at the 10% level and income per capita in the county is not statistically significant. At the same time, the interaction term between unemployment rate and income per capita is significant at the 1% level. The results suggest that if two counties have the same income per capita, the unemployment rate affects the potential-wage the FIP recipients can earn and cases living in counties with higher unemployment rates tend to earn less.

The labor force ratio in the county affects the potential-wage in the non-rural areas; the negative sign shows that relatively more labor available in the metro and urban counties is associated with lower earnings, all other conditions held constant. The result may also relate to the industry in which individuals worked, although we do not have the industry information for the FIP recipients. Many of them are likely to work in the service sector, which has a growing share of jobs in metropolitan and urban locations (Eathington, Swenson and Otto 2000).

We also include the county population share with at least a high school degree. The estimated parameter is positive and statistically significant at 1% level. The results show that the more local people that are high skilled, the higher the potential wages one can earn. The local share of poverty population in the total population is not statistically significant.

The results show that being white, male, and married are related to the potential wages. There are differences between males and females: males earn more than females.

The results can be used to show that the potential wage for the white-female is 70% that of a white-male, and 85% of a nonwhite-male. Nonwhite females earn the lowest wage in the four groups and nonwhite males earn only 83% wage of the white male. The results are consistent with Waldfogel and Mayer (1999). In their study they evaluate gender differentials in employment, annual earnings, hours worked, and hourly wages. Given the probability of work, disability is not a statistically significant determinant of wages.

Age is one of the significant variables in the wage model. The results show that potential wage will increase as the age of the case-heads approaches 50 years old., and decreases after 50. These results indicate that FIP recipients who remain employed before the age of 50 can indeed expect steady wage growth, a result expected as wages grow with job experience.

A substantial literature examines the effects of job mobility on earnings, using either regression analysis or structural modeling. For example, Topel and Ward (1992) show that about one-third of wage growth occurs at the time of job changes. Gladden and Taber (1999) find that high school dropouts who change jobs voluntarily once a year experience higher wage growth than those who stay in their old job. When a worker changes jobs, one possibility is that the worker may leave the job market; a second possibility is that the worker may have a job offer that is better than the current one. We expect positive wage gains if it is the second case. Although the data do not include information on mobility associated with working, we do have information about how many location (county) changes the FIP recipients had per year. If labor resources were fully mobile, we would expect the FIP recipients would move locations to obtain a job. We include both the indicator variables for moving once and for more than once in the equation. Only the indicator for moving once is statistically significant. The positive sign in the wage model shows that moving once in fact increases the wage income of caseheads. The indicator for moving more than once is not statistically significant although we do find a negative sign. The result is consistent with Gladden and Taber.

The effect of number of children on wage income is combined with the education level. The negative sign for the number of children in the low-skilled group indicates that children have a direct negative effect on a low-skilled woman's wages, controlling for age and location among other factors.

One of the objectives for welfare reform is to encourage financial independence and self-sufficiency for recipients. It is reasonable to assume that the participants will leave the program if they achieve these goals. The negative sign for the number of active months they stayed in the program in the last six months shows that it is difficult to achieve these objectives: people with relatively more FIP support receive lower wages.

The statistical significance of the inverse Mill's ratio shows that the selection problem on labor market participation is important here. The results suggest that when predicting the max-wage, we need to consider the problem of selection; otherwise the results are biased. This is because we do not know which recipients will be participating in the labor market when we only observe those who worked when we collected the data.

We also include indicator variables for the max-wage quarter and year. All of them are statistically significant. The results show that the potential wage is higher than other times if the max-wage quarter is between April and September (quarters three and four). At the same time, the wage at the end of the two-year period was higher than that between October 1993 and September 1994 (the first year).

Probability-of-FIP-exiting

The effect of county unemployment rate is negative and statistically significant at the 10% level in predicting being out of FIP the quarter following the max-wage. The negative sign shows that individuals are most likely to stay in FIP in the counties with higher unemployment rates than in other counties with lower unemployment rates. Not surprisingly, the positive sign for predicted max-wage shows that the higher the potential wage made by the case-heads, the more likely the case head is to leave FIP. The results also show that the potential wage has a higher effect on the cases within the high-skilled group. Previous studies on welfare participation find higher wage income, higher education, being male and white are related to higher exit rates. Brandon(1995), and Sandefur and Cook (1997) found that important determinants of recidivism (returning to welfare) include having fewer years of education, not being married, and having little job experience

According to our results, being married increases the likelihood of leaving FIP. Male-white-headed cases are more likely to leave the program after they earn the potential wage. Disability decreases the possibility of exiting the FIP. The indicator for the presence of younger children is not statistically significant.

Age is one of the significant variables in our model. Results show that recipients may leave the program after the age of 30 years old. The results may be associated with the age of younger child(ren). If a household no longer includes having children in the home, the household is ineligible for FIP. In the sample, 46.87% case-heads are between 21 and 30, 33.46% between 31 and 40, and 9.49% recipients are between 41 and 50. Only 4.22% recipients are older than 50. In general, our results are consistent with those of Cao (1996) who finds that initial welfare dependency and recidivism are correlated with the recipient's age, years of education, marital status, ethnic origin, and region.

Exiting food stamps is positively associated with exiting FIP. In other words, those leaving the food stamp program when they earn the highest wage income are also more likely to leave FIP.

The negative sign between active time in the FIP in the past half year and the probability of exiting shows the existence of " negative duration dependence". That is, reentry rates fall as the duration of the spell off of welfare lengthens (and, exit rates fall, the longer the spell of assistance) (Jensen, Keng, and Garasky,2000).

We include several terms about the effects of child support received. The results show that there are no differences between the low-skilled group and high-skilled groups related to child support. Cases are more likely to leave the program as the child support increases if they receive less than 316.95 ($) per quarter. The results relate to the number of children and the distribution of the quantity of child support. In the data, child support is larger than 316.95 ($) per quarter in only 77 cases ; more than 50% of these 77 cases have more than two children. In contrast, only 32.86% of cases that have child support less than 316.95 ($) per quarter have more than two children.

We expect FIP participants would move locations to obtain a job and that coincident with the change in location would be a change in FIP status. The results are statistically significant for the indicator of moving once and insignificant for more than once. Cases moving only once in the year are actually more likely leave FIP while those moving more than once in a year do not leave FIP. One caveat to these results is that those moving more than once to get a job may in fact go back to their hometown after they spend some time in another place. Jensen, Keng and Garasky (2000) found that for those starting in metro counties, 69.20% were active in FIP after the move to a different county and for those starting in non-metro counties, only 63.60% of were active in FIP after they moved. Porterfield (1998) found that rural families are more likely to enter welfare due to decreases in earnings or income (compared with urban families), but urban families were more likely to exit welfare through earnings or income increases.

Discussion and Conclusions

In the study, we use fractional imputation to fill in the missing education status and examine the relationship between welfare participation and employment to evaluate the factors that affect labor participation, potential wage and FIP participation. The evidence shows declining caseloads and increasing work effort among single mothers. Those who are nonwhite are more impacted by the labor market environment.

Educational attainment (of a high school degree) is one of the major factors determining labor participation, especially for single parents. Although the results show that the cases leave the labor market if at higher levels of child support, on further investigation of the relationship between child support and education attainment, we find that labor participation is more sensitive to the child support for the high skilled group than low skilled group. We find that local labor force ratio and poverty ratio in the total population are more important than local unemployment rate for the labor participation, especially in non-rural areas. Our results also show that labor force mobility is one method for welfare recipients to get a job.

Analysis of potential wages shows that cases being white, married, having higher education, and fewer children for low-skilled cases, have a higher potential wage. The FIP participants moving once per year experience a higher potential wage than those moving more than once per year and or those staying in their old jobs. FIP participants can achieve higher wages through selective moving. Analysis of FIP exiting cases shows that the higher potential wage income had a significant and positive effect on next quarter FIP status. The status in food stamp assistance program is similar to the change in FIP status. Caseloads that left the FIP also left the food stamp program. The results indicate that the objectives of welfare reform should not only include getting a job, but should also support earning more wage income. Assistance with moving may increase the wage and help recipients to achieve the aim of self-sufficiency.

Location affected the labor force participation and potential wage but did not affect the FIP status. In general, caseloads living in the non-rural counties are more likely to find a job and earn a higher potential wage. However, for countries with similar labor force share of the total population, cases living in the non-rural areas (i.e., metro and urban areas) are less likely to get a job or earn a higher potential wage. The results provide evidence that job holding and benefits (wage) could be better for FIP residents in some rural areas than others, and indicate the importance of demographic and other factors in determining the economic outcomes for these low-income cases.

The unemployment rate did not affect the FIP labor participation but did affect the potential wage and FIP status. The negative sign in the wage and exiting equations indicates that recipients will have lower earnings and be less likely to leave the FIP when facing higher unemployment rate in the county. However, the county working-age population ratio is more important than the unemployment rate for FIP labor force participation.

Education is another important factor in labor participation, potential-wage and FIP status. Those with higher education are more likely to get a job, earn higher wage and finally leave the program. And, the benefits of higher education also magnify the positive effects of higher wages in leaving FIP. It is difficult to achieve these goals for low-skilled people. The finding reiterates the need to train the low-skilled group so that they can acquire skills to get a job and earn more income. The different prospects for high-skilled and low-skilled welfare recipients reminds us that the design of welfare policy programs should consider the characteristics of the welfare recipients and the nature of jobs available to the less-skilled workers.

The empirical analyses presented here provide a preliminary indication of the effects of welfare reform. Because we only have two-years data and the period accompanies one of the longest strong economic situations in the country, analysis with later data may provide additional information on program effects under less favorable conditions. Because we can not separate economic growth factors from program and policy effects, we do not know whether the behavior of the FIP recipients will change if they face a more difficult economic climate. We do find evidence that some programs for education, job training and assistance with mobility will have positive returns relative to the objectives of welfare reform.

Table 1 FIP Caseload Statistics

Demographic Variables	Quarters: Q1	Q8
Total Caseloads	32783	32783
Education Attainment:		
With a high school degree (%)	62.14	65.12
(Standard Error)	(0.004)	(0.004)
Areas of Residence:		
Metro (%)	53.06	56.54
Urban (%)	41.95	39.28
Rural (%)	5.00	4.18
Number of Children:	2.17	2.27
(Standard Error)	(1.31)	(1.35)
No Child (%)	0.32	1.08
Less than Three Children (%)	68.51	64.93
Married (%)	19.50	23.38
Single Father (%)	3.91	
Mean Family Quarterly Wage Earnings:(100$)	16.47	26.98
(Standard Error)	(14.91)	(18.97)
No Wage Income (%)	45.13	30.49
Mean Child Support	344.17	622.40
(Standard Error)	(3.67)	(5.25)
No Child Support (%)	46.89	50.59
Local Quarterly Unemployment Rate (%)	3.74	3.26
Gender and Ethnicity:		
White (%)	84.58	
Female (%)	90.74	
Disabled (%)	23.64	
Male X Disabled (%)	3.22	
Female X Disabled (%)	20.42	
Male X Disabled X White (%)	2.68	
White X Female (%)	76.60	
White X Male (%)	7.98	
Months Stayed in FIP (standard error)	17.14(0.04)	
1-6 Months (%)	13.33	
7-12 Months (%)	15.98	
13-18 Months (%)	15.73	
19-24 Months (%)	54.96	
Months Stayed in the Food Stamp (standard error)	16.99(0.05)	
0 Months (%)	7.61	
1-6 Months (%)	8.85	
7-12 Months (%)	12.23	
13-18 Months (%)	13.50	
19-24 Months (%)	57.81	

Table 2. Working participation for the cases with children

	Single:					*Married:*				
	Low-skilled		High-skilled			Low-skilled		High-skilled		
Quarters	Total	Ratio (% Working)	Total	Ratio (% Working)	t-value	Total	Ratio (% Working)	Total	Ratio (% Working)	t-value
Male:										
Q1	654.30	55.83	1089.10	53.86	0.80	443.90	52.35	828.90	55.58	-1.10
Q2	602.90	51.65	1085.10	50.47	0.47	429.60	52.84	890.40	52.79	0.02
Q3	591.10	60.11	1071.90	57.81	0.91	428.70	60.04	893.30	60.74	-0.24
Q4	583.70	65.44	1070.80	63.88	0.64	434.90	62.91	906.10	66.48	-1.28
Q5	593.30	65.03	1137.70	64.89	0.06	403.50	62.35	858.50	64.58	-0.76
Q6	572.80	61.85	1073.20	61.38	0.19	418.70	63.12	919.30	64.80	-0.59
Q7	566.60	66.13	1073.40	65.52	0.25	420.40	65.20	923.60	67.01	-0.65
Q8	561.80	67.52	1074.20	66.63	0.36	420.80	67.32	924.20	69.32	-0.73
Female:										
Q1	9415.30	51.06	15143.00	54.35	-5.02	1864.70	63.42	3239.80	63.82	-0.29
Q2	8755.90	48.52	14992.10	52.70	-6.22	1961.50	61.58	3875.50	63.30	-1.28
Q3	8648.70	54.62	14928.30	58.38	-5.61	1970.70	66.96	3895.30	67.71	-0.58
Q4	8582.00	59.55	14977.50	62.82	-4.94	2019.20	71.62	3971.80	70.82	0.64
Q5	8714.10	61.49	15515.90	64.81	-5.12	1794.60	71.17	3517.40	70.56	0.46
Q6	8392.90	60.10	14996.10	63.90	-5.73	2039.70	70.79	4079.30	71.88	-0.88
Q7	8350.10	64.03	14955.90	67.54	-5.39	2047.20	73.16	4127.80	75.30	-1.80
Q8	8270.90	66.08	14924.10	69.22	-4.88	2068.70	74.89	4183.30	76.01	-0.97

Note: t-value refers to two-sample t-test. We test whether there is a difference between low-skilled and high-skilled group. The fractional number of cases is due to the imputation method.

Table 3 Estimated coefficients for working, max-wage and FIP-exiting equation

	Working	Max-Wage	FIP-Exit
Intercept	0.573	2.730	-0.542**
	(1.085)	(2.067)	(0.272)
(1)Location (rural=0)	1.723*	4.545**	0.080
	(1.055)	(2.171)	(0.075)
(2) County Unemployment Rate	-0.001	-0.116*	-0.079*
	(0.041)	(0.066)	(0.044)
(1)X (2)	0.027	0.087	-0.051
	(0.042)	(0.060)	(0.046)
(3)Income Per Capita		-0.079	
		(0.071)	
(1) X (3)		0.003	
		(0.072)	
(2) X (3)		-0.026***	
		(0.007)	
(4) Ratio of Population Between 18 and	1.780	4.687	
64 in the County with Total Population	(1.868)	(3.269)	
Location X (4)	-3.136*	-8.799**	
	(1.832)	(3.823)	
(5) Ratio of Poverty Population with	-0.076***	-0.080	
Total Population in the County	(0.018)	(0.051)	
Location X (5)	-0.014	0.037	
	(0.019)	(0.050)	
County Population Ratio with		0.019***	
At Least a High School Degree		(0.006)	
Active month stayed in the FIP	-0.010**	-0.187***	-0.643***
For last 6 months	(0.005)	(0.012)	(0.008)
Age		0.085***	0.029***
		(0.017)	(0.008)
Age X Age (*10)		-0.009***	-0.005***
		(0.002)	(0.001)
Marriage(married=1)	0.266***	0.366***	0.188***
	(0.030)	(0.133)	(0.038)
Times of moving in the year	0.341***		
	(0.044)		
Moving Once Indicator		0.403**	0.131*
		(0.159)	(0.071)
Moving More Than Once		-0.313	-0.059
		(0.236)	(0.170)
Child support	1.089***		1.941***
	(0.187)		(0.227)
Child support X Child support	-0.162*		-0.306***
	(0.096)		(0.110)
Child support X Education indicator	-0.269**		-0.029
	(0.127)		(0.095)

Table 3. (continued)

Education indicator	0.109***	0.697***	0.0757**
	(0.028)	(0.128)	(0.030)
Number of children	0.241***		
	(0.010)		
Education X Number of Children		0.350***	
		(0.079)	
(6)Predicted wage			0.109***
			(0.029)
Education X (6)			0.064**
			(0.034)
Indicator of at least a child with	-0.2195***		-0.020
6 year old	(0.022)		(0.032)
Disable indicator (disable=1)	-0.297***	0.161	-0.430***
	(0.028)	(0.205)	(0.138)
Gender (male=1)	0.110	0.665***	0.105
	(0.106)	(0.189)	(0.132)
White	0.282***	0.560***	0.163***
	(0.033)	(0.167)	(0.049)
Male X White	-0.207*	-0.433***	0.206
	(0.113)	(0.1899)	(0.144)
Food Stamp Participation			2.790***
			(0.045)
Inverse Mill's Ratio		-2.885***	
		(0.831)	
Quarter two Indicator		-0.141***	0.043
		(0.064)	(0.065)
Quarter Three Indicator		0.163***	-0.691***
		(0.048)	(0.041)
Quarter four Indicator		0.295**	0.484***
		(0.041)	(0.039)
Year Indicator for 1993		-0.273***	0.094***
		(0.028)	(0.031)
Log Likelihood	-33834.899		-17573.436
Adjusted R-Square		0.081	
Method	Logistic	Reg	Logistic

Note: *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

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