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Abstract

This paper uses an unbalanced panel dataset to evaluate how repeated job search services (JSS) and other personal characteristics affect the quarterly earnings of the prime-age female welfare recipients in the State of Washington. We propose a joint dependent framework for the probability of employment and potential earnings or hours or hourly wage rates to facilitate the investigation of the issues of joint determination of employment and potential earnings and to allow for factors to have different impacts on employment status and on quarterly earnings. We have also suggested formulae to compute the dynamic impact of JSS on duration and earnings. Both the maximum likelihood (ML) and semi-parametric estimates are provided. We find that the results are sensitive to the choice of models and estimation methods. For a randomly assigned individual, the first, second and the three or more JSS raised the short-run and long-run earnings by (5%, 0%, 0%) and (1%, 0%, 0%), respectively, based on the MLE and by (56.6%, 36.2%, 36.9%) and (50.7%, 36.2%, 36.9%), respectively based on the semiparametric Tobit model. We have also conducted specification analysis. The results appear to favor semi-parametric Type II Tobit model estimates.

1 Introduction

As part of welfare reform that aims to get welfare recipients employed and stay off unemployment, Washington State has introduced the WorkFirst program for recipients of TANF (Temporary Assistance to Needy Families) clients in 1997. The WorkFirst program begins with trainings in job search (Job Search Services) and allows the recipients to take the Job Search Services repetitively. Since over seventy percent of the entrants to welfare are former TANF recipients and the average annual cost per case is high ($12,363 in 1998), it is important to know if such services fundamentally changed the labor market outcomes. Hsiao, Shen, Wang and Weeks (2005) have investigated whether it is efficient to provide Job Search Services (JSS) to the same welfare recipients repetitively by considering the probability of employment. Their results show that the first JSS does have positive and significant impacts on the employment rate of those who are initially unemployed. However, providing repeated JSS to the same clients have no significant impact. Neither does any JSS to those who are already employed have any significant impacts on the probability of staying employed.

The issue of sequential treatments are very complicated from an intertemporal optimization framework. Most literature follow the lead of Robins (1986) and Gill and Robins (2001) treating sequential treatments as some form of sequential randomization (e.g. Lechner and Miquel (2001), Lechner (2004, 2006)). Under the assumption of some form of weak or strong dynamic conditional independence, the outcomes can be measured through cross-section regressions or matching estimates for each possible state (e.g. Lechner (2004, 2006)). However, the demand on the data for the approach of treating outcomes as functions of both treatments and time factor will be huge. For instance, let 1 indicate the state of receiving treatment during the period and 0 not, the possible states for the first period are 0 and 1, for the second period are (0,0), (1,0), (0,1) and (1,1), and for the n-th period, there are 2^n possible states. Matching estimates will have to be computed for each possible state to control the confounding effects of observables that vary across individuals and over time. Therefore, for n-th period data, $\sum_{t=1}^{n} 2^t$ matching estimates will have to be computed. Such a huge number of measurements might fail to convey a clear picture to policy makers.

The purpose of this paper is to compare the outcomes of different number of treatments (*i.e.* number of JSS received) independent of the time factors. We propose to take a parametric approach to control the confounding effects of both observable and unobservable factors that may vary across individuals and over time. The study by Hsiao, Shen, Wang and Weeks (2005) focuses on analyzing the effects of JSS through their impacts on employment probability. However, it is not clear if repeated JSS indeed affect the earnings of welfare recipients, and if they do, by how much. For example, for those who are already employed, even though there is no evidence of significant impacts of JSS on employment probabilities, it is still possible that JSS helps clients to find higher paid jobs or encourage them to work longer hours, thus increasing their earnings. In this study we further evaluate the impacts of repeated Job Search Services on the quarterly earnings of prime-age (25 - 35 years old) female welfare recipients who participated in the WorkFirst program of the State of Washington.

Because earnings or hours of work are censored at zero, a standard Tobit model is sometimes used to investigate whether JSS have any impact on individuals' earnings, and if they do, whether repeated JSS help. However, such single-equation model can be subject to a number of specification errors. For instance, the probability of employment and earnings may be jointly determined, and there can be unobserved individual-specific effects that are correlated with the explanatory variables which can lead to bias in the regression estimates. Moreover, as noted by Ham and LaLonde (1996), even if training is based on random assignment, non-experimental methods will have to be used to decompose the effect of training on duration and wages.

In this paper we propose a model that treats probability of employment and earnings (or hourly wage rate and hours worked) as jointly dependent. The selection of the appropriate estimator for this system depends on if one wishes to impose parametric assumption or the correlation patterns between the errors of the employment status equation and the errors of the earnings or hours equations. If the error terms of the employment status equation are uncorrelated with those of the error terms of the earnings equation, then there is no sample selection bias. A two-part model can be estimated. Earnings or hours equations can be estimated by least squares if there are no individual-specific effects and the covariance estimator if there are. If the error terms of the two equations are correlated, joint estimation of the two equations needs to be considered. In this latter case, we provide both the maximum likelihood estimates (MLE) under the joint normality assumption and the Kyriazidou (1997) estimator without a parametric assumption about the error distribution. The advantage of Kyriazidou estimator is that it does not need to make specific joint distributional assumption and is consistent whether individual-specific effects are present or not. The disadvantages are that the impact of time invariant variables cannot be estimated and only a small percentage of available observations can satisfy her conditions. Moreover, the results of Kyriazidou estimator can be sensitive to the choice of bandwidth.

Our findings show that the repeated job search services do have positive and significant effects on quarterly earnings. Therefore, we further investigate if the impacts are on wage rates or on hours of work or both after controlling for the unobserved individual-specific effects and/or sample selection effects. We find that repeated job search services have positive and significant impacts on hours of work, but not on wage rates.

Section 2 presents the model to evaluate the impact of earnings. Section 3 briefly describes the data and summarizes the estimation procedure and the main estimation results of the impacts of repeated JSS on quarterly earnings. Section 4 provides a static analysis of the impacts of JSS on earnings as well as on working hours. Methods of evaluating the dynamic impact of JSS on employment duration and earnings and their estimates are provided in section 5. Specification analysis is presented in section 6. Conclusions are in Section 7. Detailed descriptions of our data are available upon request.

2 The Model

The nature of our data is that the starting date of clients may differ, and clients are observed for different durations. Table 1 presents how many individuals enter and leave the program in each quarter, where the second and the third columns record the numbers of individuals entering and leaving the program in each quarter, respectively. For example, 1,351 clients entered the program in the second quarter of 1998, but 327 of them never showed up in latter quarters. Let y_{it} be the dummy variable denoting the ith individual's employment status at time t, with 1 denoting employment and 0 unemployment. Let E_{it} denote the logarithm of ith individual's earning if she works. The data for employment status and earnings take the form

$$\begin{aligned} (y_{it},\ E_{it}y_{it}), \quad i &= 1, ..., N, \\ t &= t_i, ..., T_i, \end{aligned} \tag{1}$$

where t_i and T_i denote the first and the last period that relevant information about the ith individual is observed.

Corresponding to the observed $(y_{it},\ E_{it}y_{it})$ there could be three possible states– a state of employment, a state of unemployment, and potential earnings. To take account issues of sample attrition, sample refreshment and duration dependence, the state of employment and unemployment are modeled by transitional probabilities as in Hsiao, et. al. (2005). The transitional probability model can be considered as the outcomes of two potential states that are state dependent. Let the state of employment be

$$y_{it}^{1*} = \eta_i^1 \left(1 + \gamma y_{i,t-1}\right) + \mathsf{w}_{it}' \left(\boldsymbol{\delta}_1^1 + b^1 y_{i,t-1}\right) + \mathsf{D}_{i,t-1}(\boldsymbol{\delta}_2^1 + g^1 y_{i,t-1}) + v_{it}^1, \tag{2}$$

and the state of unemployment by

$$y_{it}^{0*} = \eta_i^0 \left(1 + \gamma y_{i,t-1}\right) + \mathsf{w}_{it}' \left(\boldsymbol{\delta}_1^0 + b^0 y_{i,t-1}\right) + \mathsf{D}_{i,t-1} \left(\boldsymbol{\delta}_2^0 + g^0 y_{i,t-1}\right) + v_{it}^0, \tag{3}$$

and the logarithm of potential earnings by

$$E_{it}^* = \alpha_i + \mathsf{x}_{it}' \boldsymbol{\beta}_1 + \mathsf{D}_{i,t-1}' \boldsymbol{\beta}_2 + u_{it}, \tag{4}$$

where w_{it} and x_{it} denote the $K_1 \times 1$ and $K_2 \times 1$ vectors of explanatory variables, $\mathsf{D}_{i,t-1}'$ denotes the vector of the ith client's JSS participation status before period t. $\boldsymbol{\delta}_1^1$, $\boldsymbol{\delta}_1^0, b^1$ and b^0 are $K_1 \times 1$ vector of constants, $\boldsymbol{\beta}_1$ is a $K_2 \times 1$ vector, respectively, and $\boldsymbol{\delta}_2^1$, $\boldsymbol{\delta}_2^0$, g^1, g^0, $\boldsymbol{\beta}_2$ are 3×1 vectors of parameters, η_i^1, η_i^0 and α_i represent the unobserved individual-specific effects, and the error terms, v_{it}^1, v_{it}^0 and u_{it} are assumed to be independent of w_{it}, x_{it}, $\mathsf{D}_{i,t-1}$, η_i^1, η_i^0 and α_i[1]. We define $\mathsf{D}_{i,t-1}' = (0,0,0)$ if she did not receive any JSS, $\mathsf{D}_{i,t-1}' = (1,0,0)$ if she received one JSS, $\mathsf{D}_{i,t-1}' = (1,1,0)$ if she received two JSS, and $\mathsf{D}_{i,t-1}' = (1,1,1)$ if she received three or more JSS was received before period t[2]. Because 95.38% of clients takes no more than three JSS (see Table 2 for the information on participation history for all individuals), we lump 3 and more JSS together. In other words, we will be evaluating the impacts of JSS on those who only took one JSS, those who took two JSS, and those who took three or more JSS.

[1] There is an issue of whether participation of JSS is endogeneous. Using case managers desiganation and other available socio-demographic variables that are excluded from specification (5) as instruments, the diagnostic checks conducted by Hsiao, Shen, Wang and Weeks (2005) show that conditional on x and w, we may invoke the conditional independence assumption of Rosenbaum and Rubin (1983). Furthermore, as pointed out by a referee that if JSS participation acted as a proxy for unobservables, one would expect it to affect both unemployment and employment duration, but we found that JSS decreases unemployment duration but not employment duration.

[2] As pointed out by a referee, it might also be interesting to distinguish between clients with consecutive and those with nonconsecutive JSS services given the same total number of services a clients received. However, since the time span of our sample is short, as a first-order approximation, we assume that there is no decaying effect of training.

Let

$$\begin{aligned} y_{it}^{*} &= y_{it}^{1*} - y_{it}^{0*} \\ &= \eta_i(1+\gamma y_{i,t-1}) + \mathsf{w}_{it}'(\boldsymbol{\delta}_1 + b y_{i,t-1}) + \mathsf{D}_{i,t-1}'(\boldsymbol{\delta}_2 + g y_{i,t-1}) + v_{it}, \end{aligned} \tag{5}$$

where $\eta_i = (\eta_i^1 - \eta_i^0)$, $\boldsymbol{\delta}_1 = (\boldsymbol{\delta}_1^1 - \boldsymbol{\delta}_1^0)$, $\boldsymbol{\delta}_2 = (\boldsymbol{\delta}_2^1 - \boldsymbol{\delta}_2^0)$, $b = (b^1 - b^0)$, $g = (g^1 - g^0)$ and $v_{it} = (v_{it}^1 - v_{it}^0)$. An individual is employed if $y_{it}^{1*} > y_{it}^{0*}$ and stays unemployed if $y_{it}^{1*} < y_{it}^{0*}$. Then

$$y_{it} = \begin{cases} 1, \text{ if } y_{it}^{*} > 0, \\ 0, \text{ if } y_{it}^{*} \leq 0, \end{cases} \tag{6}$$

and

$$E_{it} = \begin{cases} E_{it}^{*}, \text{ if } y_{it} = 1, \\ \text{unobserved, if } y_{it} = 0. \end{cases} \tag{7}$$

Equation (5) allows the probability of finding employment for the unemployed (P_{01}) to be different from the probability of staying on employment for the employed (P_{11}). Under the assumption that D_{it} and x_{it} are exogenous and v_{it} are independently distributed with type I extreme value distribution, the probability of $y_{it} = 1$ given x_{it}, w_{it}, $\mathsf{D}_{i,t-1}$ and $y_{i,t-1}$ is

$$\begin{aligned} &\Pr\left(y_{it} = 1 | y_{i,t-1}, \mathsf{x}_{it}, \mathsf{w}_{it}, \mathsf{D}_{i,t-1}\right) \\ =\; & \frac{\exp(\eta_i(1+\gamma y_{i,t-1}) + \mathsf{w}_{it}'(\boldsymbol{\delta}_1 + b y_{i,t-1}) + \mathsf{D}_{i,t-1}'(\boldsymbol{\delta}_2 + g y_{i,t-1}))}{1+\exp(\eta_i(1+\gamma y_{i,t-1}) + \mathsf{w}_{it}'(\boldsymbol{\delta}_1 + b y_{i,t-1}) + \mathsf{D}_{i,t-1}'(\boldsymbol{\delta}_2 + g y_{i,t-1}))} \\ =\; & F_1\left(\eta_i(1+\gamma y_{i,t-1}) + \mathsf{w}_{it}'(\boldsymbol{\delta}_1 + b y_{i,t-1}) + \mathsf{D}_{i,t-1}'(\boldsymbol{\delta}_2 + g y_{i,t-1})\right), \end{aligned} \tag{8}$$

and

$$\Pr\left(y_{it}=1|y_{i,t-1},\mathsf{x}_{it},\mathsf{w}_{it},\mathsf{D}_{i,t-1}\right) \tag{9}$$
$$= \Phi\left(\eta_i(1+\gamma y_{i,t-1})+\mathsf{w}_{it}'(\boldsymbol{\delta}_1+by_{i,t-1})+\mathsf{D}_{i,t-1}'(\boldsymbol{\delta}_2+gy_{i,t-1})\right)$$

if v_{it} follows a standard normal distribution, where $\Phi(a)$ denotes the cumulative standard normal. For the initial state, since there is no information on the previous period employment status, we approximate it by

$$y_{it_i}^{*}=Q(\underline{\mathrm{x}}_i)+v_{it_i}, \tag{10}$$

where $\underline{\mathrm{x}}_i=\frac{1}{T_i-t_i+1}\sum_{t=1}^{T_i}\mathsf{x}_{it}$. We denote the unconditional probability of finding employment by

$$P_{it_i}=\Pr\left(y_{it_i}=1|\underline{\mathrm{x}}_i\right).$$

If u_{it} and v_{it} are uncorrelated, we have a panel data two-part model. The coefficients $\boldsymbol{\beta}_1$ and $\boldsymbol{\beta}_2$ can be consistently estimated by either the least squares if $\alpha_i=\alpha_j=\alpha$, $\forall i,j$, or the standard fixed-effects estimator if $\alpha_i\neq\alpha_j$(e.g. Hsiao (2003)) conditional on those individuals with $y_{it}=1$. If u_{it} and v_{it} are correlated, then it is a generalized type II Tobit Model (Amemiya (1984), Kyriazidou (1997)). The observed data are subject to selection bias. The least squares or the fixed-effects estimator of $\boldsymbol{\beta}_1$ and $\boldsymbol{\beta}_2$ are inconsistent.

If the unobserved individual-specific characteristics affect the state of employment in the same way as the state of unemployment, $\eta_i^1=\eta_i^0$, then unobserved individual-specific effects, η_i, do not appear in the specification of (8). The diagnostic checks conducted by Hsiao, Shen, Wang and Weeks (2005) show that given $\left(\mathsf{w}_{it},\mathsf{D}_{i,t-1}\right)$ the assumption of $\eta_i=0$ appears not contradicted by the information in our data. We shall therefore assume that the unobserved individual-specific effects conditional on observed explanatory variables do not play a significant role in the probability of employment equation in our empirical analysis.

2.1 A Two-Part Model

Under the assumption that the errors are independently distributed, the likelihood function for the two-part model takes the form

$$\begin{aligned} L_1 &= \prod_{i=1}^{N} \left\{ P_{it_i}^{y_{it_i}} \left(1 - P_{it_i}\right)^{1-y_{it_i}} \prod_{t=t_i+1}^{T_i} F_1 \left(\mathbf{w}_{it}'(\boldsymbol{\delta}_1 + b y_{i,t-1}) + \mathbf{D}_{i,t-1}'(\boldsymbol{\delta}_2 + g y_{i,t-1}) \right)^{y_{it}} \times \right. \\ & \left. \left[1 - F_1 \left(\mathbf{w}_{it}'(\boldsymbol{\delta}_1 + b y_{i,t-1}) + \mathbf{D}_{i,t-1}'(\boldsymbol{\delta}_2 + g y_{i,t-1}) \right)\right]^{1-y_{it}} \times \prod_{t=t_i}^{T_i} f_2\left(u_{it}\right)^{y_{it}} \right\}, \end{aligned} \tag{11}$$

where $F(\cdot)$ denotes the cumulative distribution function of v_{it} and $f_2(\cdot)$ denotes the density function of u.

Because of the independence between v_{it} and u_{it}, the likelihood function (11) can be separated into two parts, with L_{11} denotes the part that depends exclusively on parameters characterizing (5),

$$\begin{aligned} L_{11} &= \prod_{i=1}^{N} \left\{ P_{it_i}^{y_{it_i}} \left(1 - P_{it_i}\right)^{1-y_{it_i}} \prod_{t=t_i+1}^{T_i} F_1 \left(\mathbf{w}_{it}'(\boldsymbol{\delta}_1 + b y_{i,t-1}) + \mathbf{D}_{i,t-1}'(\boldsymbol{\delta}_2 + g y_{i,t-1}) \right)^{y_{it}} \times \right. \\ & \left. \left[1 - F_1 \left(\mathbf{w}_{it}'(\boldsymbol{\delta}_1 + b y_{i,t-1}) + \mathbf{D}_{i,t-1}'(\boldsymbol{\delta}_2 + g y_{i,t-1}) \right)\right]^{1-y_{it}} \right\}, \end{aligned} \tag{12}$$

and L_{12} denotes the likelihood of earnings (4),

$$L_{12} = \prod_{i=1}^{N} \prod_{t=t_i}^{T_i} f_2\left(u_{it}\right)^{y_{it}}. \tag{13}$$

Because of the separability, maximizing L_1 is equivalent to separately maximizing L_{11} and L_{12}. When $\alpha_i = \alpha_j = \alpha$, $\forall i, j$, we estimate L_{12} by the least squares. When $\alpha_i \neq \alpha_j$, we estimate L_{12} by the covariance estimator.

2.2 A Joint Dependent Model

The fixed-effects two-part model will no longer be appropriate if the errors between (4) and (5) are correlated. Failure to take account of sample selection will lead to inconsistent estimation of the behavioral parameters $(\boldsymbol{\beta}_1', \boldsymbol{\beta}_2')'$, since $E\left(E_{it}^*|y_{it} \neq 1\right) \neq E\left(E_{it}^*\right)$. Under the assumption that (v, u) are jointly normally distributed and $\alpha_i = \alpha_j = \alpha$, $\forall i, j$, we maximize the likelihood function

$$
\begin{aligned}
L &= \prod_0 P\left(y_{it}^* \leq 0\right) \prod_1 \int_0^\infty f\left(y_{it}^*|E_{it}\right) f\left(E_{it}\right) dy_{it}^* \qquad (14)\\
&= \prod_0 \left[1 - \Phi\left(\mathsf{w}_{it}'(\boldsymbol{\delta}_1 + b y_{i,t-1}) + \mathsf{D}_{i,t-1}'(\boldsymbol{\delta}_2 + g y_{i,t-1})\right)\right] \\
&\quad \times \prod_1 \left\{ \Phi\left[\frac{\mathsf{w}_{it}'(\boldsymbol{\delta}_1 + b y_{i,t-1}) + \mathsf{D}_{i,t-1}'(\boldsymbol{\delta}_2 + g y_{i,t-1}) + \sigma_{12}\sigma_2^{-2}\left(E_{it} - \mathsf{x}_{1i}'\boldsymbol{\beta}_1 - \mathsf{D}_{i,t-1}'\boldsymbol{\beta}_2\right)}{\sqrt{1 - \sigma_{12}\sigma_2^{-2}}}\right] \right. \\
&\quad \left. \times \frac{1}{\sigma_2}\phi\left(\frac{E_{it} - \mathsf{x}_{1i}'\boldsymbol{\beta}_1 - \mathsf{D}_{i,t-1}'\boldsymbol{\beta}_2}{\sigma_2}\right)\right\},
\end{aligned}
$$

where $\prod_0$ and $\prod_1$ stand for the product over those for which $y_{it} = 0$ or 1, respectively, and σ_{12}, σ_2^{-2} denote the covariance between (u, v) and the variance of u, respectively.

If (v, u) are not jointly normally distributed or if $\alpha_i \neq \alpha_j$, we use the Kyriazidou (1997) estimator. The Kyriazidou estimator allows us to take account both the fixed effects (which can be correlated with the explanatory variables) and sample selection problems simultaneously. Furthermore, this estimator also has the advantage of not having to specify the joint distribution of (u_{it}, v_{it}) parametrically. The Kyriazidou(1997) estimator is a two-step procedure. The first step involves consistent estimation of the unknown coefficients $(\boldsymbol{\delta}_1', \boldsymbol{\delta}_2', b', g')'$ in the employment status equations (8). The behavioral parameters $\boldsymbol{\beta}$ are estimated by the weighted-least-squares:

$$
\begin{aligned}
\hat{\boldsymbol{\beta}} &= \left[\sum_{i=1}^n \frac{1}{T_i - t_i + 1} \sum_{s<t} \hat{\varphi}_{in}(\tilde{\mathsf{x}}_{it} - \tilde{\mathsf{x}}_{is})'(\tilde{\mathsf{x}}_{it} - \tilde{\mathsf{x}}_{is}) y_{it} y_{is}\right]^{-1} \times \qquad (15)\\
&\quad \left[\sum_{i=1}^n \frac{1}{T_i - t_i + 1} \sum_{s<t} \hat{\varphi}_{in}(\tilde{\mathsf{x}}_{it} - \tilde{\mathsf{x}}_{is})'(E_{it} - E_{is}) y_{it} y_{is}\right],
\end{aligned}
$$

where $\boldsymbol{\beta} =(\boldsymbol{\beta}_1', \boldsymbol{\beta}_2')'$, $\tilde{\mathsf{w}}_{it} = (\mathsf{w}_{it}', \mathsf{D}_{i,t-1}')'$, $\tilde{\mathsf{x}}_{it} = (\mathsf{x}_{it}', \mathsf{D}_{i,t-1}')'$, $\hat{\varphi}_{in}$ is a weight that declines to zero as the magnitude of the difference $((\tilde{\mathsf{w}}_{it} - \tilde{\mathsf{w}}_{is})'\hat{\boldsymbol{\delta}}_n)$ increases, where $\hat{\boldsymbol{\delta}}_n$ is a consistent estimator of $\boldsymbol{\delta} = \left(\left(\boldsymbol{\delta}_1^1 + b^1 y_{i,t-1}\right)', \left(\boldsymbol{\delta}_1^0 + b^0 y_{i,t-1}\right)'\right)'$. We choose the following kernel weights:

$$\hat{\varphi}_{in} = \frac{1}{h_n} K\left(\frac{(\tilde{\mathsf{w}}_{it} - \tilde{\mathsf{w}}_{is})'\hat{\boldsymbol{\delta}}_n}{h_n}\right), \tag{16}$$

where K is a kernel density function, and $h_n = h_0 n^{-1/(2(r+1)+1)}$, with h_0 being a starting value and r captures degree of smoothness. Following Kyriazidou(1997), we let $K(\cdot)$ be the standard normal density function and we choose h_0 to be 0.5 and 3. The idea behind this estimator is that if a welfare recipient has observations that satisfy $\tilde{\mathsf{w}}_{it}'\boldsymbol{\delta} = \tilde{\mathsf{w}}_{is}'\boldsymbol{\delta}$ and $y_{it} = y_{is} = 1$ simultaneously, then taking the difference between E_{it} and E_{is} eliminates both the unobserved individual-specific effects and the selection bias term. Therefore, applying least squares to the resulting equation will yield consistent estimator of the first-differenced subsample.

3 Empirical Impacts of JSS on Earnings

In this section we first briefly describe the data and present the Hsiao, Shen, Wang and Weeks (2005) estimation results on probability of employment under the assumption of normality[3]. We then present the estimation results from the fixed-effects two-part model and the Kyriazidou (1997) model.

3.1 The WorkFirst Program for the TANF recipients

In this subsection we briefly explain the basic content of the WorkFirst program and how clients are introduced into the Job Search Services. WorkFirst is Washington State's implementation of the Federal

[3] In Hsiao, Shen, Wang and Weeks (2005) we estimate (5) by a logit model (8). However, there is not much difference between logit and probit in binary case, but normality greatly facilites the derivation of MLE for type II Tobit model. So here we report the probit estimates rather than logit estimates.

Temporary Assistance for Needy Families (TANF) program. It is launched in August 1997 to replace the Aid to Families with Dependent Children-Jobs, Opportunities, and Basic Skills (AFDC) entitlement program. The federal TANF replaced the national AFDC after the Personal Responsibility and Work Opportunity Reconciliation Act are implemented.

The main service of WorkFirst is Job Search Assistance. Job Search Assistance may include one or more of the following forms (i) Classroom instruction; (ii) Structured job search that helps to find job openings, complete applications, practice interviews and apply other skills and abilities with a job search specialist or a group of fellow job-seekers; and/or (iii) Preemployment training; (iv) High-wage/high-demand training.

When clients first enter WorkFirst, they will work together with case managers to develop Individual Responsibility Plan (IRP). As the initial focus is to assist them in finding employment, they will be first introduced to job search. Periods of job search services may last up to twelve continuous weeks. Job search service is mandatory and can be exempted only if (i) clients find and work 20 hours or more per week at an unsubsidized job; or (ii) clients have a child under three months of age or can provide good cause for not participating; or (iii) Job search specialists have determined that clients need additional skills and/or experience, or need alternative services because of problems such as substance abuse or domestic violence. If a client has received one JSS and stays unemployed, they will be referred back to case managers, where new IRP may be developed. However, further JSS were not mandatory. It depended on the information a client delivered to the case managers. In some cases, the second JSS was not assigned, but in other cases, they could be assigned to other programs, such as alternative services, etc.

Our dataset contains information that has not been available to most of the studies based on US non-experimental training programs. Heckman, LaLonde and Smith (1998) have raised the concern of program evaluation studies based on U.S. non-experimental data that include (1) outcome variables have almost always been the annual or quarterly earnings hence no measures of hours or wages; (2) the employment measure is relatively crude; it reports whether an individual worked in a "covered" job during the year (Card and Sullivan(1988)); (3) information on duration of employment or unemployment spells is unavailable. Therefore, little is known about program impact on employment rates and transition rates out of unemployment program or wages for US program as compared with European programs. Much of the knowledge on how US programs affect such outcomes have to come from experimental evaluations (e.g. Eberwein, Ham and LaLonde(1997), Ham and LaLonde(1996)). Our dataset contains detailed information about when individuals are employed and unemployed to allow the computation of employment and unemployment spells. Further, the data contains information on earnings and working hours that allow us to distinguish if the impact of JSS on earnings is from increased productivity, or from increased working hours, or both.

We use quarterly data from the second quarter of 1998 to the last quarter of 2000 on prime-aged female TANF welfare recipients between 25 - 35 to estimate the probability of employment and earning equations. The set of conditioning variables may be classified as (i) participation of the WorkFirst program such as JSS, alternative services (AS) (for clients who could not participate JSS directly due to problems like drug abusement and family violence), and post-employment services (PS) (for clients who have got at least part time jobs) dummies; (ii) duration dependence such as number of quarters employed or unemployed; (iii) welfare history; (iv) family information such as number of adults, number of children, age of the youngest child, marital status; (v) race and ethnicity dummies for whites, blacks and Hispanic; (vi) education, measured by a dummy indicating whether one receives education over grade 12 or not; (vii) local economy such as local unemployment rate; and (viii) geographic and time dummies. A full description of these variables are presented in Table 3 and summary statistics are presented in Table 4.

3.2 Probability of Employment

Columns 1 and 2 of Table 5 present the MLE estimates for the employment status of job seekers and job holders, respectively, conditional on the employment status last period and socio-demographic variables. These results show that the first JSS does have positive and significant impact on the employment rate of those who are initially unemployed, with the coefficient of the first JSS being 0.267 and significant at 1% level, while the second and the three or more JSS do not have significant additional impacts. Translating into changes in probability of employment, the first JSS increases the probability of employment for an initially unemployed individual by 4% and further JSS have no impact at all. For job holders, however, there is no evidence that taking JSS can help them to increase the probability of retaining employment[4].

We note from Table 5 that in addition to JSS, socio-demographic variables affect one's probability of employment. For example, no matter whether one is a job seeker or a job holder, more alternative services taken in the past will lower one's probability of employment, perhaps due to personality shortcomings because those who took alternative services typically have problems of substance abuse or domestic violence, while more post employment services have positive impacts on probability of employment. There are also experience-enhancing effect that if one is a job seeker, the longer one stays unemployed, the lower the chance she will find a job, but once she is employed, her unemployment history will not have significant impacts on her probability of staying employed. On the other hand, the longer one stays employed in the past, the better one's chance to be employed. This is true for both the job seekers and the job holders. Family compositions can affect one's chance of employment, with more adult at home will lower one's chance of getting employed. We also observe that the older the youngest child, the higher the chance for the mother to be employed when she is a job seeker. Further, when the age of the youngest child is controlled, the number of children do not have significant impacts on her

[4]See Hsiao, Shen, Wang and Weeks (2004) for details in calculating the mean impacts of JSS for the initially unemployed group as well as for the overall sample.

probability of employment. The estimation also shows that less educated, married females' probability of employment are lower.

3.3 The Specification and Estimation of the Earnings Equation

The econometric literature on wage or earnings determination has for the most part been based on regression equation of the form

$$\ln E_i = f(s_i, x_i, z_i) + u_i,\ i = 1, ...n, \tag{17}$$

where $\ln E_i$ is the natural log of earnings or wages for the ith individual, s_i is a measure of school attainment, x_i indicates human capital stock of experience, z_i are other factors that may affect earnings or wages. We follow this literature for the specification of quarterly earnings equation (Mincer (1974), Berndt (1990)). The dependent variable is the natural log of quarterly earnings. The available explanatory variables include the three JSS indicators, education, and race, language, local market conditions, family composition variables, etc. Typically, age and age square are used as proxies for experience. However, our sample consists only of prime-age female over a short-term span, the experience effects could be either absorbed into the intercept term or captured by the individual-specific effects.

Table 6 presents the estimated coefficients of the least squares regression, the fixed-effects estimates of two-part model, the MLE for type II Tobit model, and the Kyriazidou (1997) estimates of generalized Type II Tobit model, respectively[5]. The least squares regression indicates that the first JSS does not have significant impact but the second one has negative and significant impact, and the three and more JSS is not statistically significant. The standard type II Tobit model indicates that JSS do not have

[5] Our model is not a simultaneous equation model, but more in the spirit of Zellner's Seemingly Unrelated Regression model, hence no exclusive restriction is needed for identification. However, to reduce the possible complication due to possible multicollinearity, it would be better to have some variables excluded from one of the equations. The excluded variables from the earnings equation are alternative services, post employment services, regional dummies, etc.

any significant impact on one's earnings conditional on employment. Both the fixed-effects estimates and the Kyriazidou estimates indicate that all three Job search services have positive and statistically significant impacts on quarterly earnings conditional on employment, where the coefficients for the first, the second, and the three or more JSS are 0.361, 0.219 and 0.333 for the fixed effects two–part model, respectively, and they are 0.40, 0.309, and 0.314 for the Kyriazidou estimator, respectively. The sharp difference between the former and the latter is probably an indication of the importance of controlling the impact of the individual specific effects.

3.4 Estimation of JSS on Wage Rates and Hours of Work Equations

As Table 6 indicates that JSS can have positive impacts on quarterly earnings, we wish to further investigate whether the JSS increases quarterly earnings by raising wage rates, or by raising working hours, or both. We therefore decompose quarterly earnings into hours and wage rates and estimate the hours and wage rates equation separately. Table 7 and Table 8 present the estimated coefficients of family composition variables, race, local market conditions, the children variable, and JSS variables for the hours equation and education, race, language, local labor market condition, and JSS variables for the wage rates equation, respectively, using two-part model with and without individual-specific effects, the MLE for standard type II Tobit, and the Kyriazidou estimator.

Table 7 indicates that all explanatory variables influence the natural log of working hours are of similar magnitude as they affect the quarterly earnings. The MLE for type II Tobit model show that JSS have no effects on hours worked. Both the fixed-effects two-part model or the Kyriazidou estimator show that JSS increase welfare recipients' working hours, with the coefficients for the first, the second, and the three or more JSS to be 0.375, 0.213 and 0.334 for the fixed effects two–part model, respectively, and 0.37, 0.284, and 0.335 for the Kyriazidou estimator, respectively. Table 8 shows that none of the models indicate significant impacts of JSS on wage rates. Based on Tables 6 -8 we find that Job Search

Services have positive impacts on quarterly earnings of the prime-age female welfare recipients mainly through increasing quarterly working hours instead of increasing wage rates.

The semi-parametric Type II Tobit model can be sensitive to the selection of bandwidths and kernels. To check the sensitivity of the estimated coefficients to the bandwidth and to the selection of the kernel, we follow Kyriazidou (1997) to try different combinations of h_0 and r in $h_n = h_0 n^{-1/(2(r+1)+1)}$, with $h_0 = 0.5$ or 3, and $r = 1, 3$ or 5, respectively. In Table 9 we present the sensitivity check of this estimator in our sample for the earnings equation. This table shows that the all three JSS have positive and significant impacts on earnings, no matter what h_0 and what order r is selected. However, the magnitudes of impacts are somewhat sensitive to the choice of bandwidth. The ranges of the coefficients of the first, the second, and the third or more JSS range are (0.397, 0.41), (0.299, 0.327), and (0.301, 0.417), respectively. In later analysis of evaluating the short-term and long term impact of JSS on earnings, we will use the estimates of 0.40, 0.309, 0.314 for the first, the second, and the three or more JSS as they appear to be the most stable one for a variety choices of h_0 and r (columns (1) - (6)).

4 Short-Term Analysis of Impacts of JSS on Earnings and Hours

In section 3 we have shown that JSS have positive and significant impacts on earnings as well as on the number of hours worked for the welfare recipients. To get an estimated average dollar figure we need to estimate individual-specific effects α_i for all individuals in the sample. Since we cannot get estimates of individual-specific effects for those who were unemployed or semi-parametric type II Tobit model, we consider instead percentage changes of clients's earnings or working hours if one takes an additional Job Search Service at the State of Washington.

Denote $P_{it}(\mathsf{D}) = \Pr(y_{it} = 1|\mathsf{x}_{it}, \mathsf{D})$, and $P_{it}(\mathsf{D}^*) = \Pr(y_{it} = 1|\mathsf{x}_{it}, \mathsf{D}^*)$,where $\mathsf{D} = [1, 0, 0]$ and $\mathsf{D}^* = [0, 0, 0]$ for evaluating the impacts of the first JSS, $\mathsf{D} = [1, 1, 0]$,and $\mathsf{D}^* = [1, 0, 0]$ for the second JSS, and $\mathsf{D} = [1, 1, 1]$, $\mathsf{D}^* = [1, 1, 0]$ for three or more JSS. Conditional on α_i for those with D, the expected earnings will be $P_{it}(\mathsf{D})\exp(\alpha_i+\mathsf{x}_{it}\boldsymbol{\beta}_1+\mathsf{D}\boldsymbol{\beta}_2)\,E(e^u)$, and for those with D^*, the expected earnings will be $P_{it}(\mathsf{D}^*)\exp(\alpha_i+\mathsf{x}_{it}\boldsymbol{\beta}_1+\mathsf{D}^*\boldsymbol{\beta}_2)\,E(e^u)$. The percentage change in earnings is

$$\begin{aligned}
& \frac{P_{it}(\mathsf{D})\exp(\alpha_i+\mathsf{x}_{it}\boldsymbol{\beta}_1+\mathsf{D}\boldsymbol{\beta}_2)-P_{it}(\mathsf{D}^*)\exp(\alpha_i+\mathsf{x}_{it}\boldsymbol{\beta}_1+\mathsf{D}^*\boldsymbol{\beta}_2)}{P_{it}(\mathsf{D}^*)\exp(\alpha_i+\mathsf{x}_{it}\boldsymbol{\beta}_1+\mathsf{D}^*\boldsymbol{\beta}_2)} \\
= & \frac{\exp(\alpha_i+\mathsf{x}_{it}\boldsymbol{\beta}_1)\left[P_{it}(\mathsf{D})\exp(\mathsf{D}\boldsymbol{\beta}_2)-P_{it}(\mathsf{D}^*)\exp(\mathsf{D}^*\boldsymbol{\beta}_2)\right]}{\exp(\alpha_i+\mathsf{x}_{it}\boldsymbol{\beta}_1)\,P_{it}(\mathsf{D}^*)\exp(\mathsf{D}^*\boldsymbol{\beta}_2)} \\
= & \frac{P_{it}(\mathsf{D})}{P_{it}(\mathsf{D}^*)}\exp(\mathsf{D}-\mathsf{D}^*)\,\boldsymbol{\beta}_2-1.
\end{aligned}$$

The expected short-run impacts of JSS on growth rate of quarterly earnings can be evaluated using

$$E\left[\frac{P_{it}(\mathsf{D})}{P_{it}(\mathsf{D}^*)}\cdot\exp(\mathsf{D}-\mathsf{D}^*)\,\boldsymbol{\beta}_2-1\right], \tag{18}$$

If sample are randomly drawn, we may proximate (18) by its sample average

$$\frac{1}{N}\sum_{i=1}^{N}\left[\frac{P_{it}(\mathsf{D})}{P_{it}(\mathsf{D}^*)}\cdot\exp(\mathsf{D}-\mathsf{D}^*)\,\boldsymbol{\beta}_2-1\right]. \tag{19}$$

Similarly, expected short-run impacts of hours equation are calculated using (19) after substituting the coefficients of JSS on Earnings with the coefficients of JSS on working hours.

Table 5 provides the estimated $P_{it}(D)$ for initially unemployed and employed individual. The $P_{it}(D)$ for a random individual is derived from the equilibrium or marginal probability using $\pi_i^1 = F_i^0/\left(1-F_i^1+F_i^0\right)$,where $F_i^s = \Pr(y_{it}=1|x_{it},y_{i,t-1}=s), s=0,1,$ (Hsiao, Shen, Wang and Weeks (2005))[6].

Table 10 presents the expected short-run impacts of the first, the second, and the three or more JSS on earnings for a random individual or those who are initially unemployed based on the estimates

[6] The marginal or equlibrium probability is derived by letting the marginal probability at time t be identical to the marginal probability at time $t-1$ when the transitional probability matrix is based on equation (8).

of two-part least squares, two-part fixed effects, type II Tobit MLE and semi-parametric type II Tobit model, respectively. This table shows that the estimated impacts of models that control for individual heterogeneity are much larger than those that do not. For initially unemployed clients, the expected short-run impacts of the first, the second, and the three or more JSS on earnings are (13.9%, -7.8%, 0%) and (13.9%, 0%, 0%) for the two-part least square model and the standard type II Tobit MLE, respectively, but they are (63.4%, 23.2%, 39.5%) and (69.9%, 36.2%, 36.9%) for the two-part fixed effects model and the semi-parametric Tobit model, respectively. For a randomly selected individuals, the impacts are (5%, -7.8%, 0%) and (5%, 0%, 0%) for the two-part least square model and the standard type II Tobit MLE, respectively, but they are (50.7%, 23.2%, 39.5%) and (56.6%, 36.2%, 36.9%) for the two-part fixed effects model and the sem-iparametric Tobit model, respectively.

Table 11 presents the expected short-run impacts of the first, the second, and the three or more JSS on working hours for a random individual or those who are initially unemployed based on the estimates of two-part least squares, two-part fixed effects, type II Tobit MLE and semi-parametric Tobit model, respectively. The magnitudes of expected impacts of JSS on working hours are similar to their impacts on earnings. For initially unemployed clients, the expected short-run impacts of the first, the second, and the three or more JSS on hours are (13.9%, -6.9%, 0%) and (13.9%, 0%, 0%) for the two-part least square model and the standard type II Tobit MLE, respectively, but they are (65.7%, 23.7%, 39.7%) and (64.9%, 32.8%, 26.5%) for the two-part fixed effects model and the semi-parametric Tobit model, respectively. For a randomly selected individuals, the impacts are (5%, -6.9%, 0%) and (5%, -6.9%, 0%) for the two-part least square model and the standard type II Tobit MLE, respectively, but they are (52.8%, 23.7%, 39.7%) and (52%, 32.8%, 26.5%) for the two-part fixed effects model and the semi-parametric Tobit model, respectively.

5 The Long-Run Impacts of JSS on Employment Durations and Earnings

The results reported in the last section provides an impact analysis in a static framework. In this section we provide an analysis of the dynamic impacts of JSS on duration of employment and earnings.

Let $P_{it,jk}$ denotes the probability of transiting from state j to state k for individual i at time t, where $j,k = 0$ or 1 with 0 denoting unemployment and 1 employment. The effect of JSS on employment duration for the ith individual can be calculated using the formula

$$S_{ij}\left(D\right) = P_{i1,j1}P_{i2,10}\cdot 1 + P_{i1,j1}P_{i2,11}P_{i3,10}\cdot 2 + P_{i1,j1}P_{i2,11}P_{i3,11}P_{i4,10}\cdot 3 + ..., j = 0, 1. \tag{20}$$

The long-term impact of JSS on the percentage increase in earnings can then be approximated by

$$\frac{1}{N}\sum_{i=1}^{N}\frac{S_i\left(D\right)}{S_i\left(D^{*}\right)}\cdot \exp\left(\left(\mathsf{D}-\mathsf{D}^{*}\right)\boldsymbol{\beta}_2\right) - 1. \tag{21}$$

When the transitional probabilities are time invariant for individual i, $P_{it,jk} = P_{i,jk}$, the expected duration of employment for a client in the initially unemployed group can be calculated using

$$\begin{aligned} S_{i0}\left(D\right) &= P_{i,01}P_{i,10}\cdot 1 + P_{i,01}P_{i,11}P_{i,10}\cdot 2 + P_{i,01}P_{i,11}^{2}P_{i,10}\cdot 3 + ... \\ &= P_{i,01}P_{i,10}\cdot \frac{1}{\left(1-P_{i,11}\right)^{2}} \\ &= \frac{P_{i,01}\left(D\right)}{1-P_{i,11}\left(D\right)}, \end{aligned} \tag{22}$$

and its long-run impact on earnings can be approximated by

$$\frac{1}{N}\sum_{i=1}^{N}\frac{P_{i,01}(D)/[1-P_{i,11}(D)]}{P_{i,01}(D^{*})/[1-P_{i,11}(D^{*})]}\exp\left(\left(\mathsf{D}-\mathsf{D}^{*}\right)\boldsymbol{\beta}_2\right) - 1. \tag{23}$$

Similarly, the long-run average change in earnings for the initially employed group is

$$\frac{1}{N}\sum_{i=1}^{N}\frac{P_{i,11}(D)/[1-P_{i,11}(D)]}{P_{i,11}(D^*)/[1-P_{i,11}(D^*)]}\exp\left(\left(\mathsf{D}-\mathsf{D}^*\right)\boldsymbol{\beta}_2\right)-1. \tag{24}$$

For a randomly selected individual, we can approximate the long-run impact by

$$\frac{1}{N}\sum_{i=1}^{N}\frac{\pi_{i,1}(D)/[1-P_{i,11}(D)]}{\pi_{i,1}(D^*)/[1-P_{i,11}(D^*)]}\exp\left(\left(\mathsf{D}-\mathsf{D}^*\right)\boldsymbol{\beta}_2\right)-1, \tag{25}$$

where $\pi_{i,1} = F_{i,0}/(1-F_{i,1}+F_{i,0})$ is the marginal (equilibrium) probability for finding employment[7].

We calculate the impacts of JSS participations on mean expected durations when we approximate $P_{it,jk}$ by $P_{i,jk}$, where w_{it} are approximated by $\underline{\mathrm{w}}_i = \frac{1}{T_i-t_i+1}\sum_{i=t_i}^{T_i}\mathsf{w}_{it}$. If one is initially unemployed, the mean duration difference from taking 1 JSS versus 0 JSS is 0.096 quarters. For a randomly selected person, the mean duration difference from taking 1 JSS versus 0 JSS is 0.084.

Table 12 presents the impacts of JSS participations on percentage increase of earnings when the transitional probabilities are treated as time invariant and time varying, respectively. We first consider the time-invariant transitional probabilities. If one is initially unemployed, the impact on percentage increase of earnings for taking the first, the second, and the three or more JSS are (2.5%, -7.8%, 0%) for the two-part least square model, (2.5%, 0%, 0%) for the standard type II Tobit MLE, (47.1%, 23.2%, 39.5%) for the two-part fixed effects model, and are (52.9%, 36.2%, 36.9%) for the semi-parametric Tobit model, respectively. For a randomly selected individuals, the impacts are (1.0%, -7.8%, 0%) for the two-part least square model, (1.0%, 0%, 0%) for the standard type II Tobit MLE, (44.9%, 23.2%, 39.5%) for the two-part fixed effects model, and are (50.7%, 36.2%, 36.9%) for the semi-parametric Tobit model, respectively. The estimated impacts are larger when transitional probabilities are allowed to be

[7] In deriving the long-run impacts, we have not attempted to discount future earnings, although they can be similarly computed with a suitable choice of discount rate.

time-varying. If one is initially unemployed, the impact on percentage increase of earnings for taking the first, the second, and the three or more JSS are (9.6%, -7.8%, 0%) for the two-part least square model, (9.6%, 0%, 0%) for the standard type II Tobit MLE, (57.3%, 23.2%, 39.5%) for the two-part fixed effects model, and are (63.5%, 36.2%, 36.9%) for the semi-parametric Tobit model, respectively. For a randomly selected individuals, the impacts are (8.4%, -7.8%, 0%) for the two-part least square model, (8.4%, 0%, 0%) for the standard type II Tobit MLE, (55.5%, 23.2%, 39.5%) for the two-part fixed effects model, and are (61.7%, 36.2%, 36.9%) for the semi-parametric Tobit model, respectively.

It is interesting to note that the short-run or immediate impacts of the first JSS on earnings are larger than the long-run impacts. This is because JSS raises the probability of employment for those who are unemployed, but not the probability of holding on to the job. In other words, JSS reduces the duration of unemployment, but not increase the duration of employment. Hence, its long-run impact on earnings is much smaller than its short-run or immediate impact.

6 Specification Analysis

Our policy analysis of the impacts of JSS on earnings are sensitive to the choice of models. In this section we provide a specification analysis. We note that Kyrizidou semi-parametric estimates are consistent with the presence of individual-specific effects and non-parametric sample selection effects, we shall therefore treat the model (3) and (4) without parametric specification of the probability distribution of (v_{it}, u_{it}) as the maintained hypothesis. The two-part least squares estimates are consistent and efficient under the assumption

$$\begin{aligned} H_0 \quad &: \quad \alpha_1 = \alpha_2 = ... = \alpha_N, \text{ and} \\ & v_{it} \text{ and } u_{it} \text{ are uncorrelated.} \end{aligned} \tag{26}$$

The two-part fixed-effects model estimates are consistent and efficient if

$$H_0^* : v_{it} \text{ and } u_{it} \text{ are uncorrelated} \tag{27}$$

holds. The MLE of standard type II Tobit model is consistent and efficient if

$$\begin{aligned} H_0^{**} \quad : \quad & \alpha_1 = \alpha_2 = ... = \alpha_N, \text{ and} \\ & (u_{it}, v_{it}) \text{ jointly normally distributed} \end{aligned} \tag{28}$$

holds.

The Hausman (1978) statistics can be constructed to test H_0, H_0^*, or H_0^{**} against the maintained hypothesis. Let $\tilde{\boldsymbol{\theta}}$ denote the coefficient estimates of ljss1, ljss2, ljss3, and unemployrate under H_0, H_0^*, or H_0^{**}, respectively, for the earnings equation, ljss1, ljss2, and ljss3 for the hour equation, and ljss1, ljss2, ljss3, unemployrate, year98, yaer99 for the wage equation, and $\hat{\boldsymbol{\theta}}$ denote the corresponding Kyriazidou semi-parametric estimates, then

$$\left(\hat{\boldsymbol{\theta}} - \tilde{\boldsymbol{\theta}}\right)' \left[cov\left(\hat{\boldsymbol{\theta}}\right) - cov\left(\tilde{\boldsymbol{\theta}}\right)\right]^{-1} \left(\hat{\boldsymbol{\theta}} - \tilde{\boldsymbol{\theta}}\right) \tag{29}$$

is asymptotically chi-square distributed with four, three and six degrees of freedom for the earnings, hours, and wage rates equation, respectively. The top part of Table 13 presents the calculated chi-square statistics for testing H_0, H_0^*, or H_0^{**} against the maintained hypothesis. For the earnings model, they all firmly reject H_0, H_0^*, or H_0^{**}. For the hours model, H_0,and H_0^{**} are rejected at 1% significance level, and H_0^* is rejected at 10% level.

We note that H_0 is nested within H_0^* conditional on v_{it} being uncorrelated with u_{it} and H_0 is nested within H_0^{**} conditional on (v_{it}, u_{it}) being jointly normal. Therefore, likelihood ratio statistics can be used for these conditional tests. The bottom part of Table 13 presents the results of these conditional tests.

These test statistics indicate that for the earnings equations, the semi-parametric type II Tobit is preferred to other estimators. For the hours equation, the semi-parametric type II Tobit prevails the two-part model without individual effects (OLS estimator) at 1% significance level, and the standard type II Tobit model, and at 10% significance level, the Hausman tests rejects the fixed-effects two-part model in favor of the Kyriazidou estimator. For the wage equation, the specification tests do not reject OLS estimator.[8] All in all, they appear to favor the semiparametric estimates. Therefore, we may tentatively conclude that the semiparametric Kyriazidou estimates provide the best approximation of the effects of repeated JSS on earnings or hours.[9]

7 Conclusion

The earlier study by Hsiao, Shen, Wang and Weeks (2005) shows that the first Job Search Services can increase the employment probabilities for an unemployed individual, but not repeated JSS, nor do they have any impact on those who are employed. In this paper we further examine how effective the Washington State WorkFirst program in accomplishing the legislative goals of increasing the earnings of prime-age female TANF recipients. We have proposed a framework to jointly evaluate the effectiveness of government sponsored employment and training programs on post-program employment rates and wages or hours of work. This framework is useful even if one only uses randomized data because as noted by Ham and LaLonde (1996), non-experimental methods must be used to decompose the effect of training on hours of work and wages.

[8] We have also checked the sensitivity of the Hausman test with regard to changes of the starting values of bandwiths and kernels and find the above result quite robust.

[9] The presence of individual-specific effects in the earnings or hours equation could be proxies for capturing the omitted experience effects.

We find that the resulting estimates are sensitive to the choice of models and estimation methods. Specification analysis appears to favor semi-parametric Type II Tobit model estimates. These estimates show that all the three Job Search Services can increase quarterly earnings conditional on employment. In the short run we find that on average the first JSS increases earnings by 69.9%, the second increases it by an additional 36.3% and the three or more by a further 36.9% for initially unemployed clients. For a random client in TANF regardless of her previous employment status, the first JSS increases earnings by 56.6%, the second JSS increases it by an additional 36.2% and the three or more JSS increase earnings by another additional 36.9%. When we decompose quarterly earnings to wage rates and working hours, we find that JSS increases earnings mainly through their impacts on increasing working hours, the first, the second, and the three or more JSS increase working hours by 64.8%, 32.8% and 26.5%, respectively, for the initially unemployed group. For a random female TANF recipient, the JSS increase working hours by 52%, 32.8% and 26.5%, for the first, second and three or more, respectively.

We have also suggested formulae to compute the dynamic impact of JSS on duration and earnings. For initially unemployed individuals, under the assumption that transition probabilities are time varying, the relative impact of the first JSS on duration of employment is 0.096 quarter. The long-run impacts of the first, the second, and the three or more JSS on percentage increase in earnings are 63.5%, 36.2%, and 36.9%, respectively. When transition probabilities are time invariant, the relative impact of the first JSS on duration is 0.025 quarter. The relative impacts on percentage increase in earnings are 52.9%, 36.2%, and 36.9%, respectively. For a randomly selected individual, the relative impact of JSS on mean duration is 0.084 quarter, and the relative impacts on percentage increase in earnings are 52.9%, 36.2% and 36.9%, respectively, when the transition probabilities are assumed time invariant. These findings suggest that overall repeated JSS are beneficial to all clients regardless of their previous employment status. These beneficial impacts are obtained through either increasing the probability of employment or through increasing working hours, or both. Furthermore, repeated JSS have much larger impacts on those who are initially unemployed than those who are initially employed, and the impact of the first JSS is also much larger than the second and the third JSS[10].

As pointed out by a referee, our results are contingent on treating training as exogenous, conditional on observables and our test for exogeneity is based on assuming that number of children and regional dummies affect training but not movements in and out of employment. However, children may affect (a) unemployment through job search, and (b) employment by increasing the probability that an individual might be forced for having to tend her kids. Further, regional dummies can affect unemployment and employment through demand conditions, which differ across regions. We find that job search services decrease unemployment duration but do not affect employment duration which corroborate with the finding of Eberwein, Ham and LaLonde (1997) with experimental data to evaluate the effect of the JTPA classroom training on disadvantaged women's employment and unemployment spell. Further, if JSS participation was acting as a proxy for unobservables, one would expect it to affect both unemployment and employment durations. In view of these, our conditional exogeneity assumption for training may be a reasonable assumption. Of course, a full investigation will have to rely on the construction of intertemporal optimization model with additional JSS contingent on the outcomes of earlier JSS (e.g., Gill and Robins (2001), Jocobsan, LaLonde and Sullivan (2004)). This is a topic deserves further study. Another limitation of our study is that we have not considered the dynamics of sequential participation. We hope to take up these issues in a further study.

[10] Our estimated impacts are significantly larger than those obtained from experimental data. However, the greater percentage increase is mainly due to the smaller magnitude of the denominator in (18)-(25). The average probability of employment is 0.47, the average duration of employment is 0.98 quarter, and the average earnings is $769.31.

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Table 1 Frequency Distribution of Individuals Entering and Leaving the WorkFirst Program

Quarter (1)	Entrance (2)	Exit (3)
1998.2	1,351	327
1998.3	1,899	615
1998.4	2,019	720
1999.1	1,521	700
1999.2	1,406	829
1999.3	1,210	963
1999.4	1,002	949
2000.1	1,000	1,173
2000.2	886	1,507
2000.3	711	1,844
2000.4	621	3,999
Total	13,626	13,626

Table 2 JSS Participation History

JSS history	Frequency	Percent	Cumulative percent
0	4,791	35.16	35.16
1	5,100	37.43	72.59
2	2,181	16.01	88.6
3	924	6.78	95.38
4	371	2.72	98.1
5	169	1.24	99.34
6	59	0.43	99.77
7	16	0.12	99.89
8	12	0.09	99.98
9	3	0.02	100
Total	13,626	100	

Table 3 Variable Definitions

Variable Category	Variable Name	Definitions
WorkFirst Participation	JSS1	Indicator for whether the first Job Search Services (JSS) had been taken before period t.
	JSS2	Indicator for whether the second JSS had been taken before period t.
	JSS3	Indicator for whether three or more JSS had been taken before period t.
	ltotAS	Total number of Alternative Services (AS) before period t.
	ltotPS	Total number of Post employment Services (PS) before period t.
Employment History	lunemploycount	Total unemployed quarters before period t.
	lemploycount	Total employed quarters before period t.
Welfare history	lafdcnow	Total quarters in AFDC and/or TANF before period t. (AFDC is the predecessor of TANF).
Family	num_adlt	Number of Adults in the Assistance Unit.
	num_chld	Number of Children in the Assistance Unit.
	Youngchld	Age of the youngest child in the Assistance Unit. Calculated based on the first quarter that WorkFirst began, 1997.IV.
	Married	Marital status. 1 indicates married.
Race	Whites	Race indicator. 1 indicates client is white.
	Blacks	Race indicator. 1 indicates client is black.
	Hispanics	Race indicator. 1 indicates client is Hispanics.
Education	grade12	Education indicator. 1 indicates client's highest grader higher than 12.
Geographic Information	region1	Location indicator. 1 indicates client is from Region 1.
	region2	Location indicator. 1 indicates client is from Region 2.
	region3	Location indicator. 1 indicates client is from Region 3.
Local economy	Unemployrate	The unemployment rate of the county that client is in.
Time	year98	Year indicator. 1 indicates the record is in year 1998.
	year99	Year indicator. 1 indicates the record is in year 1999.

Table 4 Summary Statistics for Job Seekers and Job Holders

The Employment Status Model

	The Job Seekers					The Job Holders				
Variable	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max
yit	21936	0.243	0.429	0	1	18647	0.740	0.439	0	1
ljss1	15006	0.592	0.491	0	1	11951	0.591	0.492	0	1
ljss2	15006	0.231	0.421	0	1	11951	0.215	0.411	0	1
ljss3	15006	0.089	0.284	0	1	11951	0.076	0.266	0	1
ltotAS	15006	0.863	1.182	0	9	11951	0.301	0.613	0	5
ltotPS	15006	0.054	0.262	0	4	11951	0.244	0.570	0	5
lafdcnow	15006	23.174	14.133	1	55	11951	23.937	13.974	1	55
lunemploycount	15006	2.219	1.666	0	11	11951	0.283	0.504	0	3
lemploycount	15006	0.252	0.488	0	4	11951	1.847	1.368	0	11
num_adlt	21936	1.214	0.439	0	4	18647	1.131	0.367	0	4
num_chld	21936	2.418	1.323	0	12	18647	2.385	1.260	0	12
married	21936	0.206	0.404	0	1	18647	0.144	0.351	0	1
whites	21936	0.696	0.460	0	1	18647	0.625	0.484	0	1
hispanics	21936	0.101	0.301	0	1	18647	0.136	0.343	0	1
youngchld	21936	6.773	3.799	0	20	18647	7.492	3.622	1	20
grade12	21936	0.135	0.341	0	1	18647	0.151	0.358	0	1
region1	21936	0.128	0.334	0	1	18647	0.162	0.368	0	1
region2	21936	0.128	0.334	0	1	18647	0.164	0.371	0	1
unemployrate	21936	5.525	2.310	2.566	15.871	18647	5.738	2.512	2.566	15.871
year98	21936	0.191	0.393	0	1	18647	0.158	0.364	0	1
year99	21936	0.383	0.486	0	1	18647	0.409	0.492	0	1

Table 5 Maximum Likelihood Estimations of Probability of Employment

	Probability of of of finding employment	Probability of staying employed
ljss1	0.267***	-0.079
	(0.046)	(0.048)
ljss2	0.078	-0.064
	(0.063)	(0.067)
ljss3	0.081	-0.103
	(0.087)	(0.095)
ltotAS	-0.036*	-0.085***
	(0.022)	(0.032)
ltotPS	0.178***	0.107***
	(0.064)	(0.037)
lafdcnow	-0.002	-0.002
	(0.002)	(0.002)
lunemploycount	-0.163***	-0.042
	(0.018)	(0.043)
lemploycount	0.141***	0.122***
	(0.044)	(0.019)
num_adlt	-0.193***	-0.173***
	(0.060)	(0.066)
num_chld	0.005	0.036*
	(0.017)	(0.019)
married	-0.253***	0.098
	(0.066)	(0.070)
whites	-0.084	-0.185***
	(0.058)	(0.066)
blacks	0.118	-0.121
	(0.077)	(0.081)
hispanics	0.105	0.045
	(0.071)	(0.077)
youngchld	0.020***	0.005
	(0.006)	(0.006)
grade12	0.222***	0.143**
	(0.058)	(0.063)
region1	0.222***	0.204***
	(0.064)	(0.066)
region2	0.156**	0.099
	(0.075)	(0.079)
unemployrate	-0.011	-0.027**
	(0.011)	(0.012)
year98	0.300***	0.460***
	(0.080)	(0.105)
year99	0.052	0.146***
	(0.046)	(0.048)
Constant	-0.891***	1.119***
	(0.134)	(0.145)

Standard Error in parentheses.

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 6 Estimated Behavioral Parameters
for the Earnings Equation

	(1)	(2)	(3)	(4)
ljss1	0.027	0.361***	0.038	0.400***
	(0.025)	(0.046)	(0.026)	(0.060)
ljss2	-0.081**	0.209***	-0.050	0.309***
	(0.034)	(0.043)	(0.036)	(0.054)
ljss3	-0.030	0.333***	-0.002	0.314***
	(0.049)	(0.057)	(0.051)	(0.090)
grade12	0.193***		0.089***	
	(0.031)		(0.033)	
unemployrate	-0.008	-0.002	-0.019***	-0.042***
	(0.005)	(0.012)	(0.005)	(0.015)
num_chld	0.065***	-0.066*	0.048***	
	(0.009)	(0.037)	(0.009)	
num_adlt	-0.065**	0.024	0.073**	
	(0.031)	(0.066)	(0.032)	
whites	-0.052		0.000	
	(0.032)		(0.034)	
blacks	-0.069*		-0.159***	
	(0.040)		(0.042)	
hispanics	0.086**		-0.014	
	(0.038)		(0.040)	
year98	0.013	0.214***	-0.021	
	(0.044)	(0.067)	(0.046)	
year99	-0.040*	0.083**	-0.084***	
	(0.023)	(0.034)	(0.024)	
Constant	6.911***	6.740***	7.717***	

Standard Error in parentheses.

* significant at 10%; ** significant at 5%; *** significant at 1%

Column (1): Ordinary Least Squares regression of the two-part model., Column (2): fixed-effects estimates of the two-part model., Column 3: MLE of the standard type II Tobit Model; (4) Kyriazidou generalized Type II Tobit model, normal kernel, h_0 =3, r=1.

Table 7 Estimated Behavioral Parameters
for the Hours Equation

	(1)	(2)	(3)	(4)
ljss1	0.024	0.375***	0.032	0.370***
	(0.024)	(0.047)	(0.025)	(0.062)
ljss2	-0.071**	0.213***	-0.047	0.284***
	(0.034)	(0.045)	(0.035)	(0.055)
ljss3	-0.029	0.334***	-0.018	0.235**
	(0.048)	(0.059)	(0.049)	(0.092)
num_chld	0.063***	-0.059	0.048***	
	(0.009)	(0.039)	(0.009)	
num_adlt	-0.086**	0.019	0.017	
	(0.034)	(0.069)	(0.035)	
married	0.067*	0.239**	0.093**	
	(0.035)	(0.097)	(0.036)	
whites	0.011		0.042	
	(0.032)		(0.033)	
blacks	-0.101**		-0.170***	
	(0.040)		(0.042)	
hispanics	0.092**		0.013	
	(0.038)		(0.040)	
unemployrate	0.008	0.013	-0.001	
	(0.005)	(0.013)	(0.005)	
year98	0.097**	0.318***	0.071	
	(0.044)	(0.070)	(0.045)	
year99	0.033	0.147***	-0.004	
	(0.023)	(0.036)	(0.024)	
Constant	4.790***	4.549***	5.456***	
	(0.061)	(0.146)	(0.069)	

Standard Error in parentheses.

* significant at 10%; ** significant at 5%; *** significant at 1%

Column (1): Ordinary Least Squares regression of the two-part model., Column (2): fixed-effects estimates of the two-part model., Column 3: MLE of the standard type II Tobit Model; (4) Kyriazidou generalized Type II Tobit model, normal kernel, h_0 =3, r=1.

Table 8 Estimated Behavioral Parameters
for the Wage Equation

	(1)	(2)	(3)	(4)
ljss1	-0.001	0.001	-0.001	0.011
	(0.010)	(0.020)	(0.010)	(0.037)
ljss2	0.004	0.026	0.005	0.039
	(0.013)	(0.018)	(0.013)	(0.035)
ljss3	-0.025	-0.027	-0.024	0.073
	(0.019)	(0.025)	(0.019)	(0.054)
unemployrate	-0.019***	-0.015***	-0.019***	-0.011
	(0.002)	(0.005)	(0.002)	(0.013)
grade12	0.064***		0.060***	
	(0.012)		(0.012)	
english	0.002		0.000	
	(0.018)		(0.018)	
whites	-0.044***		-0.042***	
	(0.013)		(0.013)	
blacks	0.033**		0.029*	
	(0.016)		(0.016)	
hispanics	0.018		0.013	
	(0.015)		(0.015)	
year98	-0.062***	-0.071**	-0.063***	-0.021
	(0.017)	(0.029)	(0.017)	(0.067)
year99	-0.061***	-0.063***	-0.063***	-0.048
	(0.009)	(0.015)	(0.009)	(0.030)
Constant	2.178***	2.145***	2.217***	
	(0.023)	(0.039)	(0.024)	

Standard Error in parentheses.

* significant at 10%; ** significant at 5%; *** significant at 1%

Column (1): Ordinary Least Squares regression of the two-part model., Column (2): fixed-effects estimates of the two-part model., Column 3: MLE of the standard type II Tobit Model; (4) Kyriazidou generalized Type II Tobit model, normal kernel, h_0 =3, r=1.

Table 9 Sensitivity Check of the Seimparametric Type II Tobit Model for the Earnings Equation

	(1)	(2)	(3)	(4)	(5)	(6)
ljss1	0.410***	0.400***	0.397***	0.397***	0.397***	0.397***
	(0.084)	(0.060)	(0.048)	(0.048)	(0.044)	(0.044)
ljss2	0.327***	0.309***	0.299***	0.299***	0.299***	0.299***
	(0.077)	(0.054)	(0.042)	(0.042)	(0.039)	(0.039)
ljss3	0.417***	0.314***	0.301***	0.301***	0.301***	0.301***
	(0.123)	(0.090)	(0.070)	(0.070)	(0.066)	(0.066)
unemployrate	-0.038	-0.042***	-0.042***	-0.042***	-0.042***	-0.042***
	(0.027)	(0.015)	(0.012)	(0.012)	(0.011)	(0.011)

Standard Error in parentheses.

* significant at 10%; ** significant at 5%; *** significant at 1%

Column (1):h_0 =0.5, r=1, normal kernel; column (2) h_0 =3, r=1, normal kernel; column (3), h_0 =0.5, r=3, fourt-order bias-reducing kernel，Kyriazidoud(1997)，pp. 1354; column (4): h_0 =3, r=3, fourt-order bias-reducing kernel，Kyriazidoud(1997)，pp. 1354; column (5) h_0 =0.5, r=5, sixth-order bias-reducing kernel，Kyriazidoud(1997); column (6), h_0 =3, r=5, sixth-order bias-reducing kernel，Kyriazidoud(1997).

Table 10 Estimated Short-Run Impacts on Percentage Increase in Earnings*

	JSS	average of $P_{it}(D)$ / $P_{it}(D^*)$	Two-Part Least Squares	Two-Part Fixed Effects	Type II Tobit	Semiparametric Type II Tobit
	(1)	(2)	(3)	(4)	(5)	(6)
Initially Unemployed	1	1.139	13.9	63.4	13.9	69.9
	2	1	-7.8	23.2	0.0	36.2
	≥3	1	0.0	39.5	0.0	36.9
Random Individual	1	1.05	5.0	50.7	5.0	56.6
	2	1	-7.8	23.2	0.0	36.2
	≥3	1	0.0	39.5	0.0	36.9

* The estimated coefficients of JSS are treated as zero when they are statistically insignificant.

Explanations to the calculations for short-run and long-run impacts:

Table 11 Estimated Short-Run Impacts on Percentage Increase in Hours*

	JSS	average of $P_{it}(D)$ / $P_{it}(D^*)$	Two-Part Least Squares	Two-Part Fixed Effects	Type II Tobit	Semiparametric Type II Tobit
Initially Unemployed	1	1.139	13.9	65.7	13.9	64.9
	2	1	-6.9	23.7	0.0	32.8
	≥3	1	0.0	39.7	0.0	26.5
Random Individual	1	1.05	5.0	52.8	5.0	52.0
	2	1	-6.9	23.7	0.0	32.8
	≥3	1	0.0	39.7	0.0	26.5

* The estimated coefficients of JSS are treated as zero when they are statistically insignificant.

Table 12 Estimated Long-Run Impacts on Percentage Increase in Earnings*

		JSS	average of $S_i(D) / S_i (D^*)$	Two-Part Least Squares	Two-Part Fixed Effects	Type II Tobit	Semiparametric Type II Tobit
Time Invariant transitional probabilities	Initially Unemployed	1	1.025	2.5	47.1	2.5	52.9
		2	1	-7.8	23.2	0.0	36.2
		≥3	1	0.0	39.5	0.0	36.9
	Random Individual	1	1.01	1.0	44.9	1.0	50.7
		2	1	-7.8	23.2	0.0	36.2
		≥3	1	0.0	39.5	0.0	36.9
Time Varying transitional probabilities	Initially Unemployed	1	1.096	9.6	57.3	9.6	63.5
		2	1	-7.8	23.2	0.0	36.2
		≥3	1	0.0	39.5	0.0	36.9
	Random Individual	1	1.084	8.4	55.5	8.4	61.7
		2	1	-7.8	23.2	0.0	36.2
		≥3	1	0.0	39.5	0.0	36.9

* Transitional probabilities are treated as time invariant for each individual in the calculation.

Table 13 Specification Test of Semiparametric Type II Tobit Model against other estimators for the Earnings Equation#

I. Unconditional Tests: Maintained Hypothesis: non-parametric distribution of (u_{it}, v_{it}) and the presence of individual specific effects.			
Null (1)	Earnings (2)	Hour (3)	Wage (4)
No heterogeneity, no correlation between error terms	146.04*** (0.000)	106.80*** (0.000)	5.00 (0.544)
With heterogeneity, no correlation between error terms	24.92*** (0.0001)	7.17* (0.0666)	4.92 (0.555)
Without heterogeneity, allow correlation between error terms	127.89*** (0.000)	97.73*** (0.000)	4.87 (0.560)
II. Conditional Tests			
H_0 versus H_0^*	260.47***	220.75***	6.01
H_0 versus H_0^{**}	1548.32***	1215.65***	14.51***

* significant at 10%; ** significant at 5%; *** significant at 1%

: p values in parenthesis.