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ABSTRACT

Heterogeneous Treatment and Self-Selection in a Wage Subsidy Experiment

The Self-Sufficiency Project (SSP) is a research and demonstration project that offered a generous time-limited income supplement to randomly selected welfare applicants under two conditions. The first, the eligibility condition, required that they remain on welfare for at least twelve months. The second, the qualification condition, required that they find a full-time job within twelve months after establishing eligibility. In this paper we focus on a neglected and important feature of the program, namely that the financial reward for becoming qualified is inversely related to the expected wage rate. Under very simple assumptions we show that those who have a low expected wage rate have a clear incentive to establish eligibility. Empirical non-parametric evidence strongly suggests that individuals self-select into eligibility. We jointly estimate a participation equation and a wage equation that are correlated through individual random effects. Our results show that the omission of self-selectivity into qualification translates into slightly overestimated treatment effects.

JEL Classification: I38, J31, J64

Keywords: SSP Applicant Study, heterogeneous treatment, self-selection

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1 Introduction

The Self-Sufficiency Project (SSP) includes various demonstrations that were conducted in Canada to measure the sensitivity of behavioural adjustments to various income support schemes. One of the demonstrations, the Applicant Demonstration Project, offered a generous three-year income supplement to randomly selected welfare applicants under two important conditions. The first required that they remained on welfare for at least twelve months to become eligible for the supplement. The second required that they find a full-time job and left the rolls within twelve months after establishing eligibility. Applicants randomly assigned to the control group were entitled to the regular *IA* program. One of the objectives of the Applicant demonstration was to measure the so-called "delayed exit" effect, that is the extent to which welfare applicants might delay their exit from *IA* in order to establish eligibility.

The SSP demonstrations have received widespread attention partly because of the generosity of the supplement it offered and partly because of the large behavioral responses it generated. For example, Ford, Gyarmati, Foley, Tattrie and Jimenez (2003) have found that the greatest impacts of receiving the supplement occurred in the third year of the program when the proportion of *IA* recipients was 10.3 percentage points lower for the treatment group relative to the control group. Conversely, full-time work participation rates were 11.7 percentage points higher for the treatment group compared to the control group. Moreover, the average cumulative supplement earned by treatments was about 19,500$. In addition, receipt of the supplement appears to have had some long term positive effects on work. Six years after the beginning of the experiment, full-time work participation rates were still 4.9 percentage points higher for the treatment group relative to the control group. Finally, although a number of studies have found evidence of delayed exit behavior, all agree that the effect is small (Card and Robins (2005), Berlin, Bancroft, Card, Lin and Robins (1998), Lacroix and Kamionka (2003)).

Most of the above results were derived from simple non-parametric comparisons between treatment and control groups. They do not account for the complex incentives individuals in the treatment group face. Random assignment at baseline guarantees homogeneity between control and treatment groups in terms of observable and unobservable characteristics, but it does not prevent self-selection into the various phases of the experiment or across employment/non-employment. These problems have been acknowledged for some time (*e.g.* Dubin and Rivers (1993) and Ham and Lalonde (1996) in different contexts). In a recent paper, Card and Hyslop (2005) use a dynamic discrete choice model of *IA* participation to separate total SSP effect into three different effects: (1) an incentive to remain on *IA* to gain eligibility; (2) an incentive to work in the qualification phase; (3) an incentive to choose work over *IA* in the SSP phase in order to receive the supplement. Their results show strong responses to all three incentives. They found that about two-thirds of the total SSP effect was due to shortterm incentives (qualification effect).[1] It is thus very likely that the subset of applicants who establish eligibility may be a self-selected group. Likewise, conditional on establishing eligibility, those who manage to qualify for the supplement may constitute yet another self-selected group.[2]

In this paper we focus on one important and neglected feature of the SSP program, namely that the financial reward for establishing qualification is inversely related to the expected wage rate. Thus, contrary to the aforementioned papers, we acknowledge the fact that the "treatment" is not homogeneous but is a continuum that depends on observable (human capital) and unobservable (heterogeneity) characteristics. In the most extreme case, an individual in the treatment group may deem the income supplement as non-existent because of her high expected wage rate. Under very simple assumptions about the wage offer distribution, we show that those who establish eligibility are probably a self-selected group with lower than average wage rates. Under these assumptions, we show that the impact of the financial reward on employment are likely overestimated. We provide non-parametric evidence to the effect that individuals in the treatment group self-select into different statuses. Those who do not establish eligibility (*i.e.* exit *IA* within twelve months after random assignment) earn the highest average wage rate. Irrespective of their qualification status, those who establish eligibility earn the lowest wage rates.

We investigate the impact of the SSP supplement using a gradual approach. First, we model the transitions between *IA* and employment using a simple random effects probit model. The treatment and control groups are distinguished by a series of time-varying dummy variables. Because the eligibility and qualification statuses are not modelled explicitly, the parameter estimates are similar to the so-called average treatment effects. In order to investigate the potential consequences of self-selection on the treatment effects, we next estimate a similar probit model but explicitly model the eligibility and qualification statuses. The parameter estimates are similar to the so-called average treatment on the treated effects. This model is contrasted with a specification that jointly estimates the transition model and the accepted wage rates. Both equations are correlated through their random effects and contemporaneous error terms. In the absence of self-selection into the eligibility and qualification statuses, both models should yield the same results. It turns out that accounting for the potential correlation between the wage regression and the transition model decreases slightly the estimated impact of the SSP treatment.

The paper is organized as follows. Section 2 briefly presents the SSP Applicant Demonstration and proposes a simple structural model with the necessary assumptions to give rise to self-selection into eligibility. Section 3 provides simple descriptive statistics and non-parametric

[1]Based on the Recipient Demonstration, Zabel, Schwartz and Donald (2004) have found similar results, although receipt of the income supplement was found to have had a negative impact on the probability of exiting unemployment once entitlement ended.

[2]In a recent paper which focuses on the Recipient demonstration, Bitler, Gelbach and Hoynes (2006) provide empirical evidence that high-earning treatments may be willing to accept lower-paying jobs in order to qualify for the supplement.

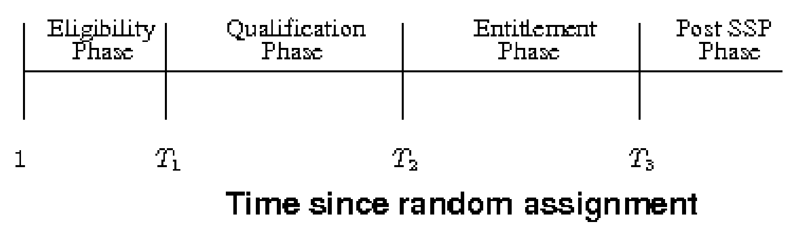
evidence on potential selectivity problems. In Section 4 we propose an econometric model that attempts to circumvent the selection issues, and whose results are presented in Section 5. Finally, we conclude the paper in Section 6.

2 The Self-Sufficiency Program

One of the objectives of the SSP Applicant demonstration was to measure the delayed exit effect associated with being offered a generous wage subsidy conditional on remaining on the welfare rolls for a minimum of 13 months (eligibility condition). It randomly sampled single parents who had applied for and received income assistance between February 1994 and February 1995 in British Columbia.[3] The program offered a generous, time-limited, monthly cash payment to all those who found full-time job and left welfare within twelve months after meeting the eligibility requirement.

Figure 1 illustrates the four phases of the SSP program. The 13-month eligibility phase is the time treatments must remain on the *IA* rolls to be eligible for potential SSP payments ($T_1 = 13$). Failure to remain at least 13 months on the rolls automatically entails disqualification.[4] The qualification phase lasts a maximum of 12 months ($T_2 \leq 25$). During that period, eligible treatments must find a full-time job (minimum 30 hours/week) and leave the rolls. Failure to find a job disqualifies them for SSP benefits. The entitlement phase starts immediately upon qualification (at month 25 at the latest) and lasts 36 months ($T_3 \leq 61$). During that period, qualified treatment earn a monthly subsidy if employed and are allowed to switch back and forth between employment and *IA* without losing qualification.

Figure 1: Time line for the SSP phases



Over the course of the entitlement (SSP) phase, the subsidy is paid out each month based on the estimated annual earnings. The subsidy is equivalent to $s(w, h) = 50\% \times (37{,}500\$ - wh)$, where w is the hourly wage rate and h is the annual hours of work. The subsidy can be

[3]To be considered as new entrants, applicants had not to have received *IA* in the six previous months. A significant minority (31%) had nevertheless received *IA* at some time in the two years prior to their current application (Berlin et al. (1998)).

[4]In fact, welfare recipients had to be on the rolls 12 out of the first 13 months after randomization. In this paper, we define eligibility has being on welfare for 13 out of the first 13 months after random assignment.

relatively large.[5] For example, an individual working 35 hours a week at 7$ per hour would have a gross earning of 12,740$ per year without SSP and 25,183$ with SSP.[6] It must be noted that the distribution of the supplement is highly skewed. Qualified treatments in the upper quartile of the distribution received on average 32,394$ over the SSP phase, while those in the lower quartile only received 6,145$ (Ford et al. (2003)).

As depicted above, the Applicant study features three different phases: Eligibility, Qualification, and Entitlement. The manner in which the phases are structured gives rise to complex incentives. To gain better understanding, a number of authors have turned to standard search models à la Mortensen (1977) to investigate potential individual responses (See, *e.g.*, Card and Hyslop(2005, 2006) and Bowlus et al. (2006)). In what follows, we briefly sketch a simple search model and underline how potential self-selection into the eligibility phase may arise.

2.1 The problem of the control group

Start first with individuals in the control group. Assume they are risk-neutral and have to choose between employment (E) and income assistance (IA), which, for simplicity, are assumed to be mutually exclusive states. Workers and welfare recipients receive job offers at a constant rate, λ, that are characterized by a wage offer, ω, drawn from a stationary distribution, $F(\omega)$, with $\omega \in [\underline{\omega}, \overline{\omega}]$. The net payoff is equal to $\omega - c$, where c represents fixed costs to work. Income assistance provides a monthly benefit equal to b. Individuals are assumed to maximize expected future income using a monthly discount rate, r. The utility derived from the job offer is compared to the utility derived from welfare. In addition, workers face an exogenous probability of losing their job, δ (job destruction rate).

Individuals are assumed to follow a reservation-wage strategy. They will reject any wage offer below their reservation wage. Workers will refuse any offer worth less than their current wage. To see this, let ω^r be the reservation wage. The expected steady-state inter-temporal utility of IA is given by:

$$(1+r)V^{IA} = b + \lambda \int_{\omega^r}^{\overline{\omega}} V^E(\omega) dF(\omega) + [1 - \lambda(1 - F(\omega^r))]V^{IA},$$

where $V^E(\omega)$ is the value of a job paying ω. The last term on the right-hand side is the value of IA assuming no satisfactory job offer was received. The value function of employed individuals is equal to:

$$(1+r)V^E(\omega) = (\omega - c) + \lambda \int_{\omega}^{\overline{\omega}} V^E(\tilde{\omega}) dF(\tilde{\omega}) + \delta V^{IA} + [1 - \delta - \lambda(1 - F(\omega))]V^E(\omega).$$

[5] The benchmark earnings was adjusted to account for increases in the cost of living and was set at 37,625$ in 1996.

[6] Some might argue that the subsidy was in fact too generous. This claim is in part corroborated by Bowlus, Lochner, Robinson and Zhong (2006) who estimate a structural search model with human capital. Their simulations show that lowering the benchmark earnings from 37,500$ to 24,000$ would have yielded the same results.

The first term on the right-hand side is the net income from a job paying ω. The second term is the marginal benefit accruing from a job offer that exceeds the current wage. The third term corresponds to the expected value of *IA* due to a job loss. Finally the last expression corresponds to the value of remaining on the same job because no satisfactory offer was received.

The reservation wage is such that $V^E(\omega^r) = V^{IA}$. By substitution, it thus follows that $\omega^r = b + c$. In other words, an individual will always refuse a job offer that does not entirely compensate *IA* benefits, b, and fixed costs, c. This results is fairly common and follows from the fact that the environment in which the individual must make decisions is in steady-state.

2.2 The problem of the treatment group

Contrary to the control group, the treatment group faces a non-stationary environment as illustrated in Figure 1. Consequently, decisions are contingent upon time and must be analyzed separately for each SSP-phase.

- *Phase 1: Eligibility*
  Phase 1 lasts $T_1 = 13$ months. Over the course of the phase individuals must compare the value of *IA* conditional on not having left *IA* once and becoming potentially qualified in *Phase 2* with that of taking a job and losing eligibility. Let $V_t^{IA,1}$ denote the value of *IA* at month t in *Phase 1*. The value functions prior to establishing eligibility are:

$$(1+r)V_t^{IA,1} = \begin{cases} b + \lambda \int_{\omega_t^{r,1}}^{\overline{\omega}} V^E(\omega)dF(\omega) + [1 - \lambda(1 - F(\omega_t^{r,1}))]V_{t+1}^{IA,1} & \text{if } t \leq T_1 - 2 \\ b + \lambda \int_{\omega_t^{r,1}}^{\overline{\omega}} V^E(\omega)dF(\omega) + [1 - \lambda(1 - F(\omega_t^{r,1}))]V_1^{IA,2} & \text{if } t = T_1 - 1, \end{cases}$$

  where $\omega_t^{r,1}$ is the reservation wage at month t of *Phase 1*, and where $V_1^{IA,2}$ is the value of *IA* in the first month of *Phase 2*. Each month $t \leq T_1 - 1$ the individual must decide whether she will accept a job starting at the beginning of next month. Acceptance is akin to refusing future SSP benefits and facing the control group's problem. The value of the job must be compared to the value of remaining an additional month on *IA* and increasing the likelihood of establishing eligibility.

  At month T_1 those who find employment starting at month $T_1 + 1$ are automatically entitled to the SSP benefit. Thus at month $T_1 - 1$ the appropriate continuation value is $V_1^{IA,2}$, the value of *IA* at the beginning of *Phase 2*, conditional on not yet being qualified.

  The reservation wage in *Phase 1* is implicitly given by:

$$V^E(\omega_t^{r,1}) = \begin{cases} V_{t+1}^{IA,1} & \text{if } t \leq T_1 - 2 \\ V_1^{IA,2} & \text{if } t = T_1 - 1 \end{cases}$$

- *Phase 2: Qualification*
  Having established eligibility, individuals must find a full-time job within 12 months in

order to qualify for SSP benefits. Prior to qualifying, the value functions are given by:

$$(1+r)V_t^{IA,2} = \begin{cases} b+\lambda\int_{\omega_t^{r,2}}^{\overline{\omega}} W^E(\omega,1)dF(\omega)+[1-\lambda(1-F(\omega_t^{r,2}))]V_{t+1}^{IA,2} & \text{if } t\le T_2-1 \\ b+\lambda\int_{\omega_t^{r,2}}^{\overline{\omega}} V^E(\omega)dF(\omega)+[1-\lambda(1-F(\omega_t^{r,2}))]V^{IA} & \text{if } t=T_2. \end{cases}$$

Here $W^E(\omega,1)$ is the value function of employed individuals receiving a wage ω with one month of elapsed benefits. Thus each month $t\le T_2-1$ the individual must compare the value of a job worth $W^E(\omega,1)$ with the value of postponing employment an additional month ($V_{t+1}^{IA,2}$). Past the qualification period, *i.e.* at $t=T_2$, the individual faces the control group's problem and the environment becomes stationary (hence the omission of time indicators on the value function V^{IA}).

The reservation wage in *Phase 2* is implicitly given by:

$$W^E(\omega_t^{r,2},1)=V_{t+1}^{IA,2} \quad \text{if } 1\le t\le T_2-1$$

- *Phase 3: Entitlement*
  Treatments who have qualified for the supplement are entitled to $T_3=36$ months of benefits. The value functions for being on *IA* are given by:

$$(1+r)V_t^{IA,3} = \begin{cases} b+\lambda\int_{\omega_t^{r,3}}^{\overline{\omega}} W^E(\omega,t+1)dF(\omega)+[1-\lambda(1-F(\omega_t^{r,3}))]V_{t+1}^{IA,3} & \text{if } 2\le t\le T_3-1 \\ b+\lambda\int_{\omega_t^{r,3}}^{\overline{\omega}} V^E(\omega)dF(\omega)+[1-\lambda(1-F(\omega^r))]V^{IA} & \text{if } t=T_3 \end{cases}$$

At $t=T_3$, the entitlement period ends and the treatment now faces the same problem a control does. The reservation wage in *Phase 3* is implicitly given by:

$$W^E(\omega_t^{r,3},t+1)=V_{t+1}^{IA,3} \quad \text{if } 2\le t\le T_3-1$$

The reservation wage profile can be easily derived from the above value functions. Note first that $W^E(\omega,1)>V^E(\omega)$, *i.e.* a *Phase 2* job with SSP benefits is worth more than a job that does not carry a bonus. It thus follows that $V_1^{IA,2}>V^{IA}$ and that $V_{t+1}^{IA,1}>V_t^{IA,1}$. Hence the reservation wage increases as the end of *Phase 1* approaches, *i.e.* $\omega_t^{r,1}<\omega_{t+1}^{r,1}$. It can also be shown that $\omega_{T_1}^{r,1}>\omega^r$ due to the fact that $V_1^{IA,2}>V^{IA}$. Thus the reservation wage increases as one nears T_1 and is necessarily higher than that of the control group at T_1. Treatments are thus expected to have lower exit rates in *Phase 1* (delayed exit effects).

The same type of reasoning applies to *Phase 2*. Indeed, because $W^E(\omega,1)>V^E(\omega)$, it follows that $V_1^{IA,2}>V^{IA}$ and $V_{t+1}^{IA,2}<V_t^{IA,2}$. In other words, access to potential benefits increases the value of *IA* at the beginning of *Phase 2*. It declines regularly as one nears T_2 due to the potential loss of SSP benefits. Because $W^E(\omega,1)$ increases with ω, this is equivalent to $\omega_t^{r,2}>\omega_{t+1}^{r,2}$, *i.e.* the reservation wage declines with t. In *Phase 3* it can also be shown that the reservation wage is constant throughout. In addition, because $V_{T_3}^{IA}=V^{IA}$ it follows that $\omega_{T_3}^{r,3}=\omega^r$. Finally, because $W^E(\omega,T_3)>V^E(\omega)$ it must be the case that prior to T_3, $\omega_{T_3-t}^{r,3}<\omega^r$. Treatments are thus expected to have higher transition rates into employment.

2.3 Selection into eligibility

The analysis so far has assumed that individuals receive wage offers that are drawn from a single distribution. As stressed by Stern and Canals-Cerda (2002), unobserved characteristics are important in explaining the behavior of workers in the labor market. For example, workers with identical observed characteristics may face different wage offer distributions and have different reservation wages due to differences in relevant unobserved characteristics. Unfortunately, very few analyzes have considered unobserved heterogeneity within the context of a search model. This is particularly important in the context of the SSP program since the incentive effects are directly proportional to the wage rate a worker is likely to receive.

Recently, a number of authors have introduced heterogeneity both on the supply side (workers) and the demand side (firms) of equilibrium search models (see Bontemps, Robin and den Berg (1999), Postel-Vinay and Robin (2002)). Others, *e.g.* Bloemem (1997), have introduced preference heterogeneity within a partial-equilibrium model. To illustrate how potential selection problems into eligibility may arise, we now assume that the wage offer distribution depends on some unobserved heterogeneity component, ε, that is drawn from a distribution with mean 0 and finite variance. We may consider ε as a productivity factor that is unobserved by the analyst but known to the individual (and valued by the market). For convenience, we may write the conditional wage distribution as $F(\varepsilon \mid \eta)$.

To fix ideas, we assume as in Bowlus et al. (2006) that workers have different (unobservable) skills and receive a wage equal to $\tilde{\omega} = \omega + \varepsilon$.[7] The unobservable component, ε, is assumed continuously distributed over $[\underline{\varepsilon}, \overline{\varepsilon}]$. The above discussion has made clear that the differences between the control and the treatment groups' reservation wage profiles hinge on the value of the SSP benefits in *Phase 3*. The value of a *Phase 3* job may be written as follows:

$$\begin{aligned}(1+r)W^E(\tilde{\omega},t) &= (\omega+\varepsilon-c) + \frac{SSP_t-\omega-\varepsilon}{2} + \lambda\int_{\tilde{\omega}}^{\overline{\omega}} W^E(\omega',t+1)dF(\omega') \\ &\quad +\delta V_{t+1}^{IA,3} + [1-\delta-\lambda(1-F(\tilde{\omega}))]W^E(\tilde{\omega},t+1).\end{aligned}$$

Obviously, individuals with large values of ε will receive a large wage offer soon after randomization. Consequently they will expect relatively low SSP benefits. For them the incentive to postpone exit from welfare in *Phase 1* is much smaller. In fact, there might exist a critical value, ε^*, such that $W^E(\varepsilon^*,1) = V^E(\omega)$. Individuals in the treatment group with $\varepsilon \geq \varepsilon^*$ thus behave no differently from those in the control group. In addition, because they typically command a greater than average wage rate, they can be expected to leave *IA* at a higher rate than controls. Likewise, one may also argue that the entitlement effect in *Phase 3* will be larger the smaller the (expected) wage offer. Indeed, individuals who expect low wage offers benefit on average from a relatively large subsidy. The converse naturally holds for those who receive high wage offers. It is thus difficult to distinguish the entitlement effect from the unobserved

[7] Alternatively, we could assume as suggested by Stern and Canals-Cerda (2002) that individuals face different wage offer distributions. We could write $F(\omega; m_i, \tau_i)$ where m_i is the location parameter of group or individual i, and τ_i is the dispersion parameter.

heterogeneity component in *Phase 3*. The problem may even be compounded if we allowed for unobserved preference heterogeneity as in Bloemem (1997) and Wolpin and Eckstein (1989).

The above discussion underlines the potential for selectivity into eligibility due to the built-in SSP incentives. Hence, the treatment group can be divided into three subgroups: those who do not establish eligibility, those who establish eligibility but do not manage to qualify and those who qualify, conditional on establishing eligibility. The main issue from a statistical point of view is to determine the distribution of ε among the different subgroups. To the extent the distribution is the same across the subgroups, a simple comparison between those who qualify and the control group would provide an unbiased estimator of the treatment effect on the treated. The above discussion suggest this is rather unlikely. In the next section we provide *prima facie* evidence on potential self-selectivity into eligibility.

3 Data

The data we use in this paper are taken from the SSP Applicant Study. Selected individuals who agreed to be part of the experiment were interviewed at home to complete a baseline survey. They were asked to sign an informed consent document that explained the nature of the experiment, described the random assignment process, and stated that all individual-level data would be kept confidential. They also had to agree to have their administrative social assistance record linked to the survey data. Immediately after the baseline interview, individuals were randomly assigned to either the treatment or the control group. The experimental sample comprises 1,648 treatments and 1,667 controls. Treatments were sent a letter and a brochure explaining their potential eligibility for an earnings supplement. They were reminded they had to remain on welfare for at least 12 months to be eligible for the supplement, and that upon establishing eligibility, they had to find a full-time job within the next 12 months to qualify for the income supplement.[8]

Four follow-up surveys were conducted 12, 30, 48 and 72 months after the baseline interview to keep track of changes in educational attainment, work-related training, employment, work experience, marital status, number of children, *etc.* Information on *IA* benefits *per se* was obtained from administrative records. Due to sample attrition, of the 3,315 original respondents in the baseline interview, only 2,015 completed all succeeding follow-up interviews. The analysis in this paper is based on this balanced panel.[9]

[8] Although SSP rules stated that qualification had to occur between months 13 and 24 after random assignment, these were interpreted rather loosely. In the data, individuals have qualified as early as month 11 and as late as month 27.

[9] We also imposed a few additional restrictions. For instance one applicant reported a negative age and 47 did not report years of experience properly. Upon deleting these 48 observations we are left with a sample of 1,967 applicants who are each observed for 71 consecutive months.

3.1 Sample statistics

Table 1 presents descriptive statistics for our sample at baseline. The first and second columns concern the control group and the treatment group as a whole. In columns (3)–(5) the treatment group is broken down into those who are unqualified, ineligible and qualified. Unqualified applicants have established eligibility but did not find a job in the qualification phase, while ineligible applicants left *IA* within 13 months and have not established eligibility.[10] Qualified applicants have established eligibility and did find a job during the qualification phase. Despite having removed nearly 40% of the original sample, columns (1) and (2) show that control and treatment groups are nearly identical.[11] Thus attrition is unlikely to affect a particular group of applicants.[12] The figures show that the mean age is about 33, that women represent about 93% of all applicants, that approximately 71% were born in Canada, and that very few had a spouse at baseline. Individuals in the sample are relatively well educated. Indeed, over 68% of them had either attended a community college or a university. Finally, roughly 41% own a car but very few own a house.[13]

Interestingly, columns (3)–(5) shows important differences. Among the unqualified group fewer are married, own a car or a house, and more are foreign born. Most importantly, the overall level of schooling and the number of years of work experience are by far the lowest among the treatment subgroups. Those in the ineligible group are slightly older, proportionately more own a car or a house and have fewer preschoolers. They are by far the best educated group among the treatment subgroups (74% have some post-secondary schooling) and have the most years of experience at baseline. Finally, the overall characteristics of those who qualified are somewhat located between those of the two previous groups. They are better educated and have more years of experience than the unqualified group but not so much as those in the ineligible group.

Table 2 is similar to Table 1 except that it focuses on labor market outcomes. The means are computed over the 72-month period of observation so that differences between the controls and treatments reflect behavioral adjustments. Interestingly, the mean hourly wage rates of the two groups are nearly identical. Yet, there is substantial variation within the treatment group. Indeed, the ineligible treatments earn an average wage rate that is 8.9% higher than the controls and as much as 26.5% higher than the qualified treatments. Assuming full-time employment (2000 hours), a qualified treatment could expect an income supplement of 10,100$. An ineligible treatment, had she qualified, could only expect 7,810$ on average. The differences in wage rates do not translate into large differences in (conditional) hours of work, as controls only work slightly more hours per month than the treatments and very little variation is

[10] Recall that we define eligibility as remaining on *IA* for the first 13 months after random assignment.

[11] Although not reported, we tested that the means of each variable in Table 1 was identical for the two groups. The null assumption was never rejected.

[12] See Hansen (2006) for a detailed analysis of the sample attrition in the SSP Applicant study.

[13] According to the provincial welfare program, the net value of houses and cars are assumed to generate a monthly income flow that contributes to the household's income. Assets are thus implicitly means-tested.

Table 1: Sample statistics: Mean individual characteristics at baseline
(Standard deviations in parentheses.)

	Control group	Treatment group			
		All	Unqualified	Ineligible	Qualified
Sample size	970	997	253	445	299
Gender (woman = 1)	0.93	0.92	0.94	0.91	0.92
	(0.25)	(0.27)	(0.24)	(0.28)	(0.27)
Age (years)	33.23	33.41	33.30	33.99	32.63
	(7.20)	(7.80)	(7.35)	(8.25)	(7.40)
Married (married = 1)	0.06	0.07	0.04	0.09	0.05
	(0.23)	(0.25)	(0.19)	(0.29)	(0.23)
Born (Canada = 1)	0.72	0.70	0.60	0.75	0.73
	(0.45)	(0.46)	(0.49)	(0.43)	(0.45)
Car (owner = 1)	0.40	0.42	0.28	0.53	0.39
	(0.49)	(0.49)	(0.45)	(0.50)	(0.49)
Home (owner = 1)	0.14	0.14	0.10	0.18	0.11
	(0.35)	(0.34)	(0.30)	(0.38)	(0.31)
Children under 7	0.89	0.86	0.99	0.73	0.94
	(0.83)	(0.81)	(0.82)	(0.76)	(0.84)
Children under 19	0.91	0.91	0.88	0.94	0.88
	(0.99)	(0.97)	(0.93)	(0.98)	(0.99)
Work experience (years)	10.99	11.25	9.30	12.56	10.93
	(7.02)	(7.44)	(6.87)	(7.85)	(6.85)
Schooling (proportion)					
No high school	0.19	0.19	0.29	0.14	0.17
	(0.39)	(0.39)	(0.45)	(0.35)	(0.37)
High school	0.13	0.14	0.17	0.12	0.14
	(0.33)	(0.35)	(0.37)	(0.33)	(0.35)
Collegial	0.52	0.53	0.44	0.55	0.56
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)
University	0.16	0.15	0.10	0.19	0.13
	(0.37)	(0.36)	(0.30)	(0.39)	(0.33)

1. When comparing unqualified and ineligible applicants, differences in means are statistically significant at 0.05 level for Work experience, Children under 7, Born, Car, Home and Schooling and at 0.10 level for Married.
2. When comparing unqualified and qualified applicants, differences in means are statistically significant at 0.05 level for Work experience, Born, Car and Schooling.
3. When comparing ineligible and unqualified applicants, differences in means are statistically significant at 0.05 level for Age, Work experience, Children under 7, Car and Home and Schooling and at 0.10 level for Married and Schooling.

observed among the treatment subgroups. Consequently, the variations in monthly earnings arise principally because of variations in the wage rates.

3.2 Wage, earnings and hours of work distributions

The figures reported in Table 2 provide some crude evidence that the establishment of eligibility may be related to expected wage rates. To investigate the matter further, Figure 2 plots the ratio of hourly wage rates of controls, ineligible treatments and unqualified treatments

Table 2: Sample statistics: Mean labor market outcomes[†]
(Standard deviations in parentheses.)

	Control group	Treatment groups			
		All	Unqualified[‡]	Ineligible	Qualified
Hourly wage	10.05	9.71	9.42	10.94	8.65
	(4.25)	(4.03)	(5.06)	(4.41)	(2.79)
Log-wage	2.21	2.19	2.13	2.30	2.11
	(0.42)	(0.38)	(0.43)	(0.43)	(0.27)
Monthly hours	138.42	133.30	132.12	133.71	133.30
	(38.50)	(34.78)	(36.01)	(36.16)	(33.01)
Monthly	1366.22	1278.13	1177.14	1444.58	1153.96
earnings	(674.99)	(592.67)	(554.45)	(672.83)	(474.68)
Monthly	7.07	7.01	6.93	7.12	6.94
log-earnings	(0.47)	(0.45)	(0.44)	(0.50)	(0.50)
Monthly SSP					700.56
benefits					(215.37)

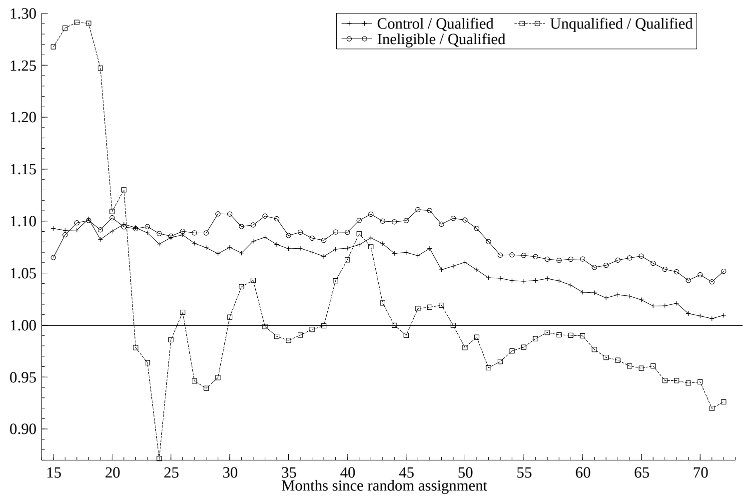
[†]Means over computed over 72 months and exclude zero values for applicants which hourly wage, hours and earnings are all three observed. Hereinafter, wage rates and earnings are expressed in 1993 constant dollars.
[‡]Few unqualified applicants work over the 72 months period of observation. Hence, we have to be careful with the interpretation of these means.

over those of the qualified treatments. The ratios are computed monthly and are reported as of month 15 after random assignment.[14] There are a number of noteworthy features in the figure. First, ineligible treatments and controls earn an average hourly wage rate that is approximately 5%-10% higher than that of qualified treatments. Second, unqualified and qualified treatments earn approximately the same average wage rate, although the relation is relatively noisy. Third, the ratios are relatively stable up to month 48. In the ensuing months the three subgroups experience a decline in their hourly wage rates relative to those of the qualified treatments. Month 48 coincides more or less to the first month at which those who qualified the earliest (around month 13) lose their SSP benefits. This could indicate that, conditional on remaining employed, the loss of benefits by the qualified treatment is partly compensated for by an increased wage rate. Finally, by the end of month 72, the controls and the qualified treatments earn the same hourly wage rate. The ineligible group on the other hand still earns approximately 6% more than the qualified treatments.

Figure 3 depicts the kernel-smoothed probability density functions of log-wages for the control group and the three treatment subgroups. The wage rates are computed as the mean of all reported individual wages over the course of the experiment. The main notable feature of this figure is that the density functions of the qualified and unqualified treatments are the most heavily skewed to the left, while the density function of ineligible applicants has a very heavy tail to the right. The figure also shows that the density function of the controls more or less corresponds to a combination of the other three curves, as should be expected. This is

[14]Too few unqualified and qualified treatments work in the eligibility phase to allow valid statistical comparisons. Likewise, relatively few unqualified treatments work prior to month 25.

Figure 2: Monthly mean-wage ratios



consistent with Table 2 which showed that the average wage rates of the control and treatment groups are nearly identical. Figure 3 highlights the fact that there is considerable heterogeneity among the treatment subgroups. It also suggests that those who end-up receiving SSP benefits are precisely those who benefit the most from the program.

Figure 3: Kernel-smoothed densities of log-wages

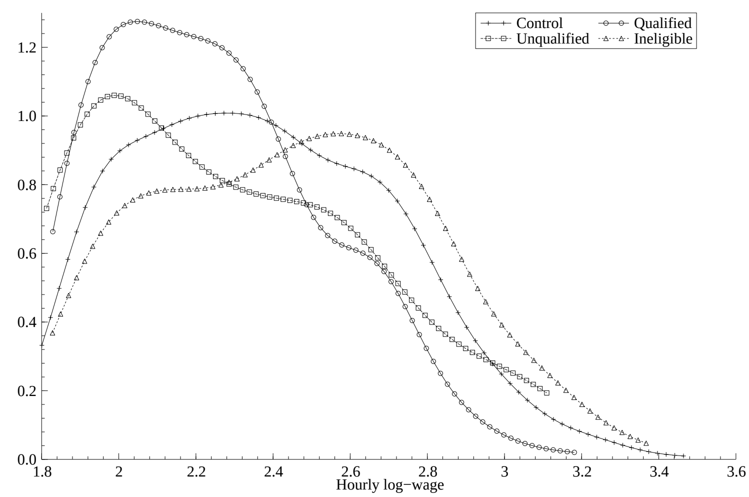
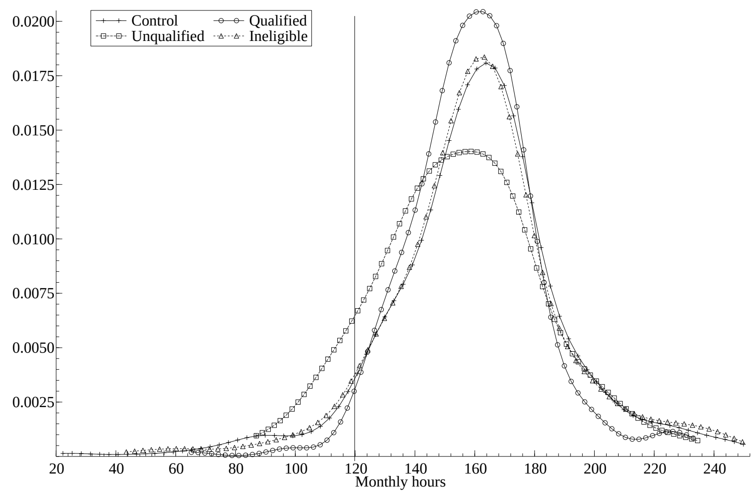


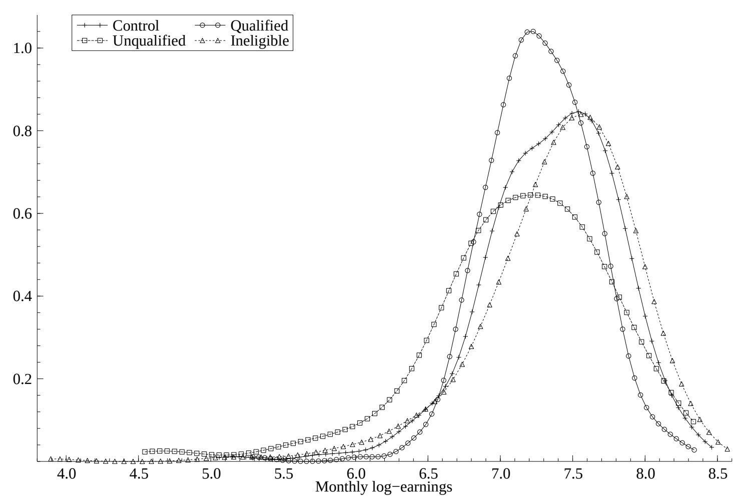
Figure 4 plots the density functions of the average non-zero monthly hours of work. The hours distribution of qualified treatments has more mass to the left of 120 hours, as required by the program. Unqualified treatments, on the other hand, have a flatter distribution with considerable mass located to the left of 120 hours, suggesting that many held part-time jobs. Finally, ineligible treatments and controls have nearly identical distributions.

Figure 4: Kernel-smoothed densities of monthly hours of work



Lastly, Figure 5 plots the probability density functions of average non-zero monthly log-earnings. Earnings are computed as the product of monthly hours of work and hourly wage rates. The figure thus summarizes the two previous ones. It unambiguously shows that qualified treatments earn less than both the controls and the ineligible treatments, while the latter earn slightly more than the controls.

Figure 5: Kernel-smoothed densities of log-earnings



The preceding figures suggest that the SSP's built-in incentives may have resulted in sorting the treatments into various subgroups with different observable and presumably unobservable characteristics. While suggestive the figures provide no formal evidence that the differences they underline are statistically significant. Table 3 reports a series of tests of equality between the probability density functions depicted in the previous figures. The test statistics are based on recent work by Li (1996).

Table 3: Equality of Distributions: Li's Statistics†
(Bandwidth in parentheses)

	Log-wages	Hours		Log earnings	
	Months 1–72	Months 1–72	Months 61–72	Months 1–72	Months 61–72
Qualified vs control	5.559	0.918	0.576	6.176	2.226
	(0.096)⋆	(7.363)	(9.490)	(0.127)⋆	(0.153)⋆
Qualified vs ineligible	13.123	0.258	-0.068	12.523	3.985
	(0.096)⋆	(7.363)	(10.387)	(0.127)⋆	(0.175)⋆
Qualified vs unqualified	1.654	2.155	0.570	3.283	0.877
	(0.096)⋆⋆	(7.363)⋆	(11.324)	(0.127)⋆	(0.175)
Control vs unqualified	2.774	1.640	-0.775	2.724	0.597
	(0.097)⋆	(8.495)	(9.490)	(0.136)⋆	(0.153)
Control vs ineligible	1.714	-0.767	0.214	1.422	1.854
	(0.097)⋆⋆	(8.495)	(9.490)	(0.136)	(0.153)⋆⋆
Unqualified vs ineligible	4.222	1.547	0.182	5.077	3.947
	(0.117)⋆	(9.520)	(10.387)	(0.179)⋆	(0.186)⋆

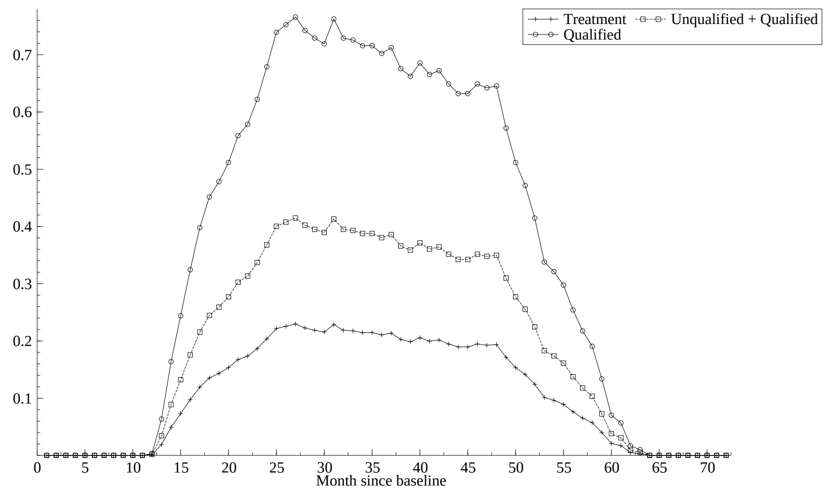
†The test compares $H_0 : \hat{f}(x^f) = \hat{g}(x^g)$ to $H_1 : \hat{f}(x^f) \neq \hat{g}(x^g)$. The test statistic is $\sim N(0,1)$. Probability density functions are statistically different at 0.05 level (⋆) and at 0.10 level (⋆⋆).

The first column of the table reports test results for various combinations of log-wage densities over the 72-month window. According to the table, all the distributions are distinct. Column (2) compares monthly hours of work over the same 72-months window while column (3) focuses on the year that followed the last month of SSP receipt (months 61 to 72). Interestingly, column (2) shows that the null assumption that the distributions are identical is only rejected when comparing qualified and unqualified treatments. Likewise, Column (3) concludes that the hours distribution are identical for all pairwise comparisons in the months that followed the end of the experiment. Columns (4) and (5) are similar to the two previous ones but focus on earnings instead. The earnings distributions combine monthly hours of work and hourly wage rates. Not surprisingly it is found that most distributions are different both over the 72-month window and in the year that followed the experiment.

3.3 Participation in work and income assistance

Despite its generosity, relatively few treatments receive the SSP supplement at any given month. Figure 6 plots the monthly proportion of SSP receipt among the various treatments subgroups. Overall, only approximately 20% of all treatments benefit from the supplement at any given month. The figure rises to 35% for those who have established eligibility (qualified and unqualified treatments), and rises further to 70% for qualified treatments. On average, qualified treatments receive the supplement during 26 months out of a maximum of 36.

Figure 6: Monthly receipt rates of SSP, by group



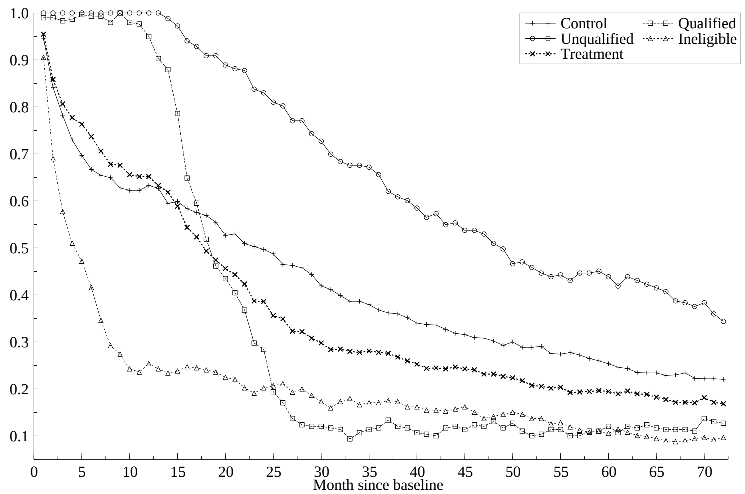
Figures 7 and 8 provide *prima facie* evidence of behavioral response to the SSP incentives. Figure 7 depicts the monthly *IA* participation rates. The vast majority of the ineligible treatments leave *IA* within the first few months following random assignment.[15] Only about 40% of the controls do so over the same period. The figure also shows considerable heterogeneity among eligible treatments. Once they have established eligibility, the participation rates of qualified applicants decrease drastically and remain at the same low level as that of ineligible treatments for the remainder of the experiment. However, unqualified treatments leave *IA* at a much lower rate and their participation rates always remain above that of the controls.

Figure 8 plots the monthly participation rates on the labor market. The figure does not perfectly mirror the previous one since a number of individuals are neither working or on the rolls in a given month.[16] Participation rates of qualified treatments increase dramatically once they establish eligibility. Nearly none of unqualified treatments report working in the eligibility phase. Their participation rates increase steadily at the same rate as that of the control group's members but always remain the lowest. The proportion of qualified treatments that are active on the labor market, while decreasing past the qualification phase, is higher than that of the controls well past the end of the experiment. This result is similar to what has been found by others using slightly different samples (*e.g.* Card and Hyslop (2006)). On the other hand,

[15]By definition all the ineligible treatments have left *IA* during the eligibility phase. The fraction on *IA* never reaches 0 because a small fraction moves back and forth between *IA* and *W*.

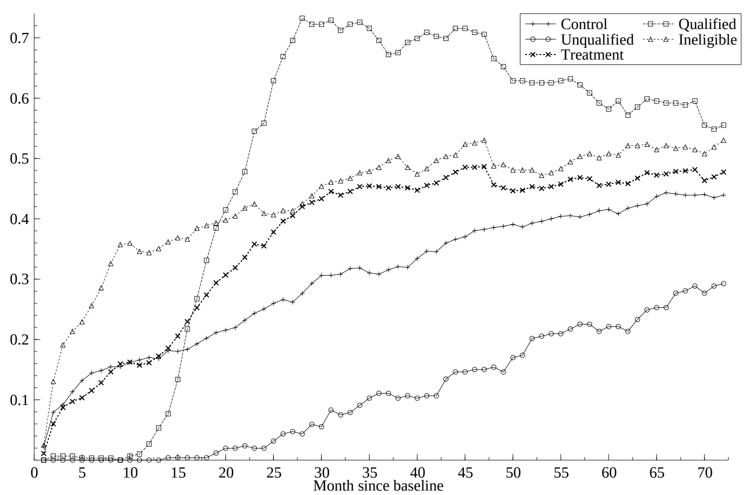
[16]Adding the curves vertically may sum to less 100%. It indicates that some have left *IA* for reasons that are not related to work (*e.g.* marriage, *etc.*)

Figure 7: Monthly *IA* participation rates



the participation rates of qualified and ineligible treatments are very similar in the last few months of observation.[17]

Figure 8: Monthly labor market participation rates



[17] The participation rates in months 69–72 are not statistically different at the 5% level of significance.

4 Empirical specification

The theoretical model and the empirical evidence of the previous sections have highlighted the fact that the establishment of eligibility may be correlated with expected wage rates. As argued in section 2, these are potentially determined by unobserved individual effects. Likewise, the decision to leave *IA* may also be affected by unobserved individual effects, irrespective of treatment status, that are correlated to those that determine the wage rates. Omission of these unobserved effects will likely lead to biased parameter estimates of the treatment effects.

The empirical model we propose integrates these individual effects in an attempt to control for selection bias into eligibility. The model focuses on the monthly transitions between *IA* and work. Both states are assumed mutually exclusive and exhaustive.[18] Let

$$y_{it}^{\star} = \mathbf{z_{it}}\delta + \alpha_i + \xi_{it} \tag{1}$$

be a latent variable measuring the (indirect) utility of working relative to IA, where $\mathbf{z_{it}}$ is a vector of exogenous variables, α_i is the individual effect, and ξ_{it} is a contemporaneous error term. The observable model is given by:

$$y_{it} = \begin{cases} 1 & \text{if} \quad y_{it}^{\star} > 0 \\ 0 & \text{if} \quad y_{it}^{\star} \leq 0. \end{cases}$$

The (log)wage equation is specified as

$$\omega_{it} = \mathbf{x_{it}}\beta + \eta_i + \zeta_{it}, \tag{2}$$

where $\mathbf{x_{it}}$ is a vector of exogenous variables, η_i is the individual (unobserved) effect, and ζ_{it} is a contemporaneous error term. In order to identify the model we must make a number of assumptions about the stochastic structure. First, we assume that the contemporaneous error terms and the individual fixed effects are not correlated within and across equations (1) and (2):

$$\text{cov}(\xi_{it}, \alpha_i) = \text{cov}(\xi_{it}, \eta_i) = \text{cov}(\zeta_{it}, \alpha_i) = \text{cov}(\zeta_{it}, \eta_i) = 0 \quad \forall t.$$

To be consistent with the theoretical model, we assume that the unobserved heterogeneity terms are correlated:

$$\begin{pmatrix} \alpha_i \\ \eta_i \end{pmatrix} \sim N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_\alpha^2 & \sigma_{\alpha\eta} \\ \sigma_{\alpha\eta} & \sigma_\eta^2 \end{pmatrix}\right]. \tag{3}$$

[18] Welfare claimants are entitled to work a limited number of hours each month. As such *IA* and work are not entirely exclusive states. We abstract from this possibility and consider the state to be *IA* in a any given month if the individual receive *IA* benefits, irrespective of her working status. As argued by Card and Hyslop (2006),

> "A limitation of our modeling approach is the narrow focus on welfare participation, rather than on a broader set of outcomes, such as welfare and employment status. Over most of the sample period the time profiles of experimental impacts on welfare participation and full-time employment are mirror images. Thus we believe that our basic findings can be translated directly into implications for employment".

Likewise, the error terms ξ_{it} and ζ_{it} are also assumed to be correlated:

$$\begin{pmatrix} \zeta_{it} \\ \xi_{it} \end{pmatrix} \sim N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_\zeta^2 & \sigma_{\zeta\xi} \\ \sigma_{\zeta\xi} & \sigma_\xi^2 \end{pmatrix}\right]. \tag{4}$$

A priori we expect the correlation $\sigma_{\alpha\eta}$ to be positive because high-productivity individuals (large η_i) probably have a greater attachment to the labor market (large α_i). Conditional on η_i and α_i, $\sigma_{\xi\zeta}$ may capture the correlation between aggregate demand and supply shocks on wages and employment. It is thus difficult to sign $\sigma_{\xi\zeta}$ *a priori*. All the parameters are identified save for the variance of the latent equation (1) which we set to one ($\sigma_\zeta^2 = 1$).

The sample at our disposal can be divided into three parts.[19] The first regime is composed of all those who work full-time in a given month and whose wage rates are observed. The probability of this occurring is given by:

$$\begin{aligned} P_{it}(R_1 \mid \alpha_i, \eta_i) &= \int_{-a}^{+\infty} g(\xi_{it}, \zeta_{it} \mid \alpha_i, \eta_i) \mathrm{d}\xi_{it} \\ &= \int_{-a}^{+\infty} f(\zeta_{it} \mid \alpha_i, \eta_i) f(\xi_{it} \mid \zeta_{it}, \alpha_i, \eta_i) \mathrm{d}\xi_{it} \\ &= \frac{1}{\sigma_\zeta}\phi\left(\frac{\zeta_{it}}{\sigma_\zeta} \mid \alpha_i, \eta_i\right) \Phi\left(\frac{a + \rho\zeta_{it}}{\sqrt{1-\rho^2}} \mid \zeta_{it}, \alpha_i, \eta_i\right), \end{aligned} \tag{5}$$

where $a = \mathbf{z_{it}}\delta + \alpha_i$, $\rho = \sigma_{\zeta\xi}/\sigma_\zeta$ is the correlation between ζ_{it} and ξ_{it}, g is the bivariate normal density, f is the univariate normal density, ϕ is the standard normal density and Φ is the normal cumulative distribution. The second regime refers to those who work in a given month but whose wage rates are not reported:

$$\begin{aligned} P_{it}(R_2 \mid \alpha_i, \eta_i) &= \int_{-a}^{+\infty} \int_{-\infty}^{+\infty} g(\xi_{it}, \zeta_{it} \mid \alpha_i, \eta_i) \mathrm{d}\zeta_{it} \mathrm{d}\xi_{it} \\ &= \int_{-a}^{+\infty} f(\xi_{it} \mid \alpha_i, \eta_i) \mathrm{d}\xi_{it} = \Phi(a \mid \alpha_i, \eta_i). \end{aligned} \tag{6}$$

Finally, the last regime relates to those who do not work in a given month:

$$\begin{aligned} P_{it}(R_3 \mid \alpha_i, \eta_i) &= \int_{-\infty}^{-a} \int_{-\infty}^{+\infty} g(\xi_{it}, \zeta_{it} \mid \alpha_i, \eta_i) \mathrm{d}\zeta_{it} \mathrm{d}\xi_{it} \\ &= \int_{-\infty}^{-a} f(\xi_{it} \mid \alpha_i, \eta_i) \mathrm{d}\xi_{it} = \Phi(-a \mid \alpha_i, \eta_i). \end{aligned} \tag{7}$$

[19] The sample comprises 1,957 individuals. We removed 10 eligible treatment who have worked during qualification but did not receive SSP benefits. Each individual is observed for 71 months. Thus there are 138,947 contributions to the likelihood function. The three regimes account for 43,304, 3,953 and 91,690 contributions, respectively.

By integrating over the whole domain of ξ_{it} we implicitly assume that those who do not work in a given month did not receive a job offer. The likelihood function of our sample is given by:

$$\log L(\mathbf{x_{it}}, \mathbf{z_{it}}; \delta, \beta, \Sigma) = \sum_{i=1}^{N} \log \int_{\alpha_i} \int_{\eta_i} \prod_{t=1}^{T} \prod_{j=1}^{J} \left[P_{it}(R_j \mid \alpha_i, \eta_i) \right]^{\mathbb{I}(R_j)} g(\alpha_i, \eta_i) \mathrm{d}\alpha_i \mathrm{d}\eta_i,$$

where $N = 1957$, $T = 71$, $J = 3$. Σ includes all identified parameters in (3) and (4). Finally, $\mathbb{I}(R_j)$ is an index function equal to 1 if regime j is chosen, 0 otherwise, and $P_{it}(R_j \mid \alpha_i, \eta_i)$ is one of (5), (6) or (7). The parameter estimates are obtained by the method of simulated maximum likelihood (see *e.g.* Train (2003)).[20]

5 Results

Three different specifications of the model are estimated. The first focuses on the so-called average treatment effect. The eligibility and qualification statuses are not explicitly taken into consideration. Rather, treatments and controls are only distinguished through a series of interaction dummy variables that vary across the various phases of the experiment. This specification is based upon equation (1) only. The vector $\mathbf{z_{it}}$ includes demographic variables and the treatment dummy variables. Models 2 and 3 focus on the treatment effect *per se*. In both cases, eligibility and qualification statuses are explicitly modelled. Both specifications aim at measuring the impact of SSP receipt on the transitions into employment. Model 3 jointly estimates the wage and the participation equations while Model 2 focuses on the participation equation alone. The latter model thus implicitly imposes the correlation between α_i and η_i to be zero. A comparison of the two models will underline the consequences of neglecting potential self-selection into eligibility on the measured treatment effect.

All three specifications include numerous parameter estimates. These are spread over four tables to ease comparison across models. Table 4 focuses on the impact of the demographic variables on employment. The parameter estimates of all three models are relatively similar qualitatively and most have the expected sign. The education variables need be interpreted relatively to high-school. Not surprisingly, more schooling is strongly associated with higher transition rates into employment.[21] Likewise, more work experience and owning a car or a house at baseline is also associated with a higher participation rate.[22] As expected, households with more preschoolers and teenagers are less likely to work. Employment is found to be seasonal, being lowest in the Winter and highest in the Fall. Dummy variables are used to proxy the yearly fluctuations in the business cycle. The parameter estimates show that the

[20]The estimations are based upon 500 random Halton draws.

[21]Surprisingly, Model 3 predicts that those who hold a university degree have lower transitions rates into employment.

[22]The latter two variables may potentially be endogenous. We did investigate this issue and found no evidence of endogeneity biases. Further, removing the two variables from the regression has no impact whatsoever on the remaining parameter estimates.

two years during which the experimental sample was recruited (1994 and 1995) are those during which finding a job was hardest. After 1996, it appears as tough *IA* recipients had an easier time finding a job despite the fact that unemployment rates was not lower and that women's employment rates were stable between 1994 and 2000.[23,24] In fact, higher participation rates may partly be explained by the tightening of *IA* requirements that were introduced by the government of British Columbia in 1996. Finally, it is found that employment depicts considerable state dependence. Being employed in the previous month significantly increases the probability of employment in the current month.

5.1 Estimation of the Treatment Effects

Table 5 focuses on the treatment effects. As mentioned previously, Model 1 estimates the average treatment effect. Recall from our theoretical discussion that treatments are expected to delay exit from *IA* in order to establish eligibility. As shown in the lower panel, all three treatment effects in the eligibility phase are indeed negative. During the qualification phase (months 13–24), treatments have a lower probability of working in the first quarter but a larger one in the following two quarters. These results are also consistent with our theoretical discussion. Finally, between months 25 and 60, which more or less corresponds to the entitlement phase, treatments are found to have significantly higher participation rates. Once the experiment has ended (months 61+), both groups appear to behave similarly.

The marginal treatment effects are reported in Table 6. The lower panel shows that the treatments have a lower participation rate of approximately 1.5 percentage points each quarter of the eligibility phase. This figure is very close to those reported by Card and Hyslop (2006) and Lacroix and Kamionka (2003). During the qualification phase, treatments have marginally lower participation rates in the first quarter and marginally higher rates in the next two quarters. Likewise, treatments exhibit larger but decreasing participation rates in the entitlement phase. The average marginal treatment effect is approximately 5 percentage points.[25] The estimated marginal treatment effects are smaller than what would be expected from inspection of Figure 8. To understand why this is so, Figure 9 draws the predicted participation rates of treatments and controls as well as the predicted participation rates of treatments had they not received SSP benefits. The predicted participation rates closely mimic the observed participation rates of both groups (not shown). The model, on the other hand, predicts that qualified treatments would have had higher participation rates than controls in the absence of financial incentives. It thus appear that treatments very likely self-select into qualification and as a consequence controls do not constitute a proper counterfactual group.

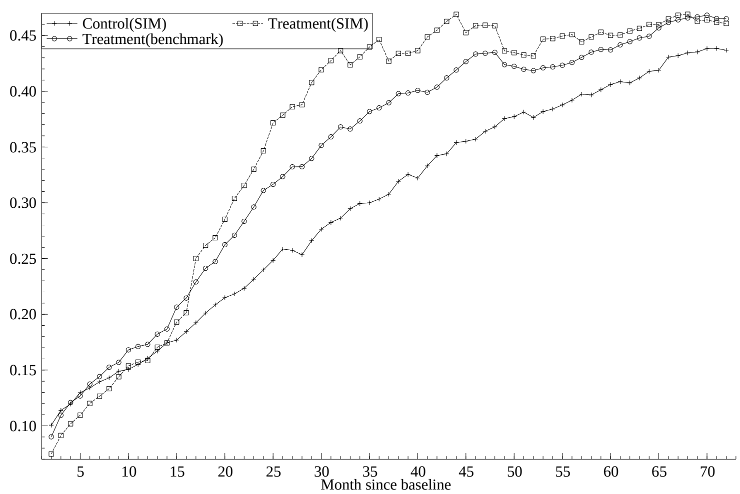
Model 2 explicitly accounts for the endogeneity of the eligibility and qualification statuses. The model does not take into account the selection process based on the wage rates. Recall that

[23]Unemployment rates in the Vancouver area were 8.6%, 7.9%, 7.9%, 8.2%, 8.0%, 7.7% and 5.8% for 1994 to 2000 respectively. Source: Statistics Canada, Table 282-0091.

[24]Ford et al. (2003), page 11.

[25]This estimate is very similar to the one reported by Lacroix and Kamionka (2003) using a duration model.

Figure 9: Actual and Predicted Participation Rates - Model 1



a treatment must have remained on *IA* for the first 13 months following random assignment to be considered eligible. Conversely, an ineligible treatment must have left *IA* for a full-time job within the first 13 months following random assignment. We thus define the eligibility status as follows:

$$\text{Eligible}_{it} \quad = \quad \begin{cases} 1 & \text{for } 13 < t \leq \min[T^Q, 25] \\ 0 & \text{otherwise,} \end{cases}$$

where T^Q is the month in which the individual establishes qualification. Likewise, the ineligibility status is defined as:

$$\text{Ineligible}_{it} \quad = \quad \begin{cases} 1 & \text{for } T^I < t \leq 71 \quad \text{if } y_{iT^I} = 1 \text{ with } 1 \leq T^I \leq 13 \\ 0 & \text{otherwise.} \end{cases}$$

Thus a treatment who is observed working at month T^I in the first 13 months following randomization becomes ineligible as of T^I and remains so for the remainder of the experiment. Finally, a qualified treatment is one who has found a job at month $T^Q \leq 25$ and has left the rolls.[26] SSP entitlement is thus defined as:

$$\text{SSP}_{it} \quad = \quad \begin{cases} 1 & \text{for } T^Q < t \leq (T^Q + 35) \\ 0 & \text{otherwise} \end{cases}$$

We also define two additional dummy variables to capture behavioral adjustments once eligibility and entitlement statuses expire. First, an unqualified treatment is one who has established

[26] The dummy variables are set equal to one in the month that follows the establishment of a given status. Thus, for example, the eligibility status is set to zero from months 1 to 13 and set to one as of month 14 if the individual remained on the rolls without interruption. Likewise, the variables denoted "Ineligible × Month" and "SSP" are set to one only in the month that follows the entry into full-time employment.

eligibility but who did not find a job during the qualification phase,*i.e.*

$$\text{Unqualified}_{it} \;=\; \begin{cases} 1 & \text{for } 25 < t \leq 71 \quad \text{if Eligible}_{i25} = 1 \\ 0 & \text{otherwise.} \end{cases}$$

A qualified treatment may change his behavior once the entitlement period is over. To capture this we define the following dummy variable:

$$\text{PostSSP}_{it} \;=\; \begin{cases} 1 & \text{for } (T^Q + 35) < t \leq 71 \\ 0 & \text{otherwise.} \end{cases}$$

The parameter estimates of the second column of Table 5 relate to Model 2. The specification includes a series of interaction variables to allow as much flexibility as possible. The regression includes dummy variables for the eligibility, unqualified, ineligibility and entitlement statuses. Hence the parameter estimates need to be interpreted relative to the control group. Eligible treatments have lower participation rates in the qualification phase and during the following two years. Indeed, the parameter estimates associated with the variables Eligible, "Unqualified×25-36" and "Unqualified×37–48" are negative and statistically significant. Those who manage to qualify and receive SSP benefits have much higher participation rates both during and after the entitlement phase. The gap between their participation rates and those of the control group slowly tapers off once the phase has ended, as shown by the parameter estimate of "Post-SSP × Trend". Finally, the ineligible group, those who have left the rolls prior to establishing eligibility, also have much higher participation rates than the controls. The parameter estimates are all positive and statistically significant but tend to decrease almost linearly in time.

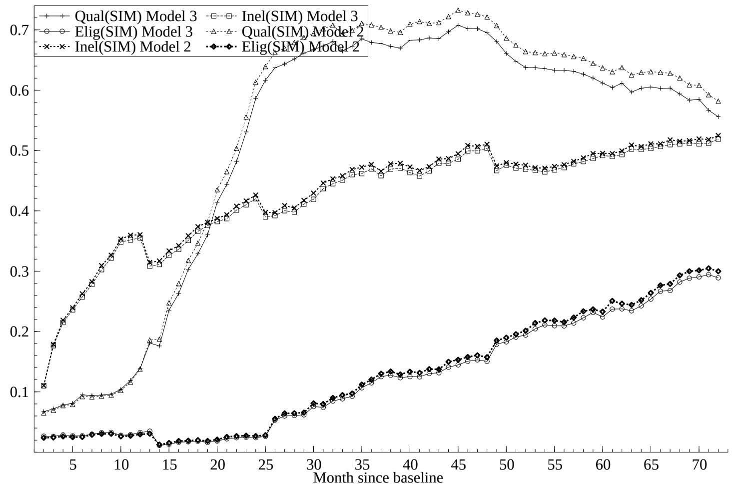
The parameter estimates of the third column of Table 5 relate to Model 3. Qualitatively, the parameters of Models 2 and 3 are relatively similar. On the other hand, the parameters associated with the unqualified variables in Model 3 are larger in absolute value while those associated with the SSP and Ineligible variables are smaller. The top panel of Table 6 reports the estimated marginal treatment effects of both models. As shown, Model 2 slightly overestimates the exit rates of eligible and unqualified treatments. It also overestimates the exit rates of qualified and ineligible treatments by a few percentage points. Figure 10 reports the predicted participation rates of Models 2 and 3 side by side. Both models mimic the observed participation rates relatively well (not shown). The figure shows that the predictions of Model 2 always lay above those of Model 3. Because the counterfactual rates of both models are almost identical, the marginal effects of Model 2 are always greater than those of Model 3.

The difference between the two models is entirely driven by the correlation between the wage equation and the participation equation. The parameters of the wage equation are reported in Table 7. Most parameter estimates have the expected sign and magnitude. Hence, more schooling and experience is conducive to a higher wage rate.[27] Interestingly, unqualified

[27] Experience is time dependent. It is computed as follows:

$$\text{Experience}_{it} = \text{Experience}_{i0} + \sum_{l=1}^{t-1} y_{il},$$

Figure 10: Predicted Participation Rates - Models 2 & 3



treatments command the lowest monthly wage rate which is between 7.3% and 14.4% lower than the wage received by the control group. Qualified treatments also receive a lower wage. During the entitlement phase, their wage rate is roughly 2.7% lower. This is consistent with the theoretical results that showed that SSP benefits could result in lower reservation wages. Furthermore, in the post-SSP phase the wage rates of the controls and the qualified treatments are essentially identical. Again, this is consistent with the theoretical model. The parameter estimates also indicate that there is very little difference between the wages ineligible treatments and controls receive. The differences depicted in Figures 2 and 3 are thus probably entirely due to differences in the observable and unobservables characteristics of each group.

Finally, Table 8 reports the Cholesky decomposition of the covariance matrix and the covariance matrix *per se*. The parameter estimate of $\sigma_{\alpha\eta}$ is large and positive. We must thus conclude that high-productivity individuals also appear to have greater attachment to the labor market.

All in all, our empirical findings concur with the theoretical model presented in Section 2. The built-in incentives of the SSP program induce recipients to self-select into eligibility and qualification. Consequently, those who end-up receiving SSP benefits are not representative of the population of welfare recipients. They have lower expected wage rates and less human capital than recipients who exit *IA* prior to establishing eligibility. On the other hand, those who establish eligibility but never qualify have the lowest level of human capital and probably have weaker preferences for work according to the parameter estimates. By neglecting the selectivity into the program, Model 2 produces biased estimates the participation equation. The parameter estimates of both the demographic variables and the treatment effects differ substantially from those of Model 3. Thus the treatment effect measured under Model 2 is

where Experience_{i0} is the number of months of experience at baseline.

slightly overestimated because it omits the fact that qualified treatments with higher wage rates are also more attached to the labor market. Once we account for individual fixed effects, this bias washes away.

6 Conclusion

The Applicant Study of the Self-Sufficiency Project aimed at measuring the responsiveness of welfare applicants to a generous and time-limited income supplement. Randomly selected applicants had to meet two conditions to receive the supplement. The first, the eligibility condition, required that they remained on welfare for at least twelve months. The second, the qualification condition, required that they find a full-time job within twelve months after establishing eligibility and left the rolls.

The SSP demonstration has received widespread attention partly because of the generosity of the supplement it offered and partly because of the large behavioral responses it generated. Most papers that assess the impact of the SSP nevertheless neglect one important feature of the program, namely that the financial reward for becoming qualified is inversely proportional to the expected wage rate. In this paper we acknowledge the fact that the "treatment" is not homogeneous but is a continuum that depends on potential wage rates. Using a search-theoretical framework, and under very simple assumptions about the wage distribution, we show that those who have a low expected wage rate have a clear incentive to establish eligibility. Consequently, those who eventually receive the SSP supplement may constitute a highly selected group among the treatment group.

Empirical non-parametric evidence strongly suggests that treatments self-select into eligibility. We thus specify an econometric model that simultaneously estimate the choice of working full time and the level of individual wage rates. The two equations are correlated through individual effects and through contemporaneous shocks. We find mild evidence that treatments self-select into eligibility and qualification. Once we properly account for the selection issue, the treatment effects decrease slightly but remain important.

References

Berlin, G., W. Bancroft, D. Card, W. Lin, and P. K. Robins (1998) ‘Do work incentives have unintended consequences ? Measuring ”Entry Effects” in the Self-Sufficiency Project.’ SRDC Report

Bitler, M.P., J.B. Gelbach, and H.W. Hoynes (2006) ‘Distributional impacts of the Self-Sufficiency Project.’ SRDC Working Paper 06-01

Bloemem, H.G. (1997) ‘Job search theory, labour supply and unemployment duration.’ *Journal of Econometrics* 79, 305–325

Bontemps, C., J.-M. Robin, and G.J. Van den Berg (1999) ‘An empirical equilibrium job search model with search on the job and heterogeneous workers and firms.’ *International Economic Review* 40(4), 1039–1074

Bowlus, Audra, Lance Lochner, Chris Robinson, and Yahong Zhong (2006) ‘Human Capital and Search Behavior.’ SRDC Working Paper 06-10

Card, D., and D.R. Hyslop (2005) ‘Estimating the effects of a time-limited earnings subsidy for welfare leavers.’ *Econometrica*

— (2006) ‘Understanding the dynamic effects of the SSP applicant study.’ SRDC WP 06-03

Card, David, and Philip K. Robins (2005) ‘How important are “entry effects” in financial incentive programs for welfare recipients? Experimental evidence from the Self-Sufficiency Project.’ *Journal of Econometrics* 125, 113–139

Dubin, Jeffrey A., and Douglas Rivers (1993) ‘Experimental estimates of the impact of wage subsidies.’ *Journal of Econometrics* 56, 219–242

Ford, Reuben, David Gyarmati, Kelly Foley, Doug Tattrie, and Liza Jimenez (2003) ‘Can work incentives pay for themselves? Final report on the Self-Sufficiency Project for welfare applicants.’ SRDC Report

Ham, John C., and Robert J. Lalonde (1996) ‘The effect of sample selection and initial conditions in duration models: Evidence from experimental data on training.’ *Econometrica* 64(1), 175–205

Hansen, Jorgen (2006) ‘The effects of human capital and earnings supplements on income assistance dependence in Canada.’ SRDC Working Paper 06-05

Lacroix, Guy, and Thierry Kamionka (2003) ‘Assessing the impact of non-response on the treatment effect in the Canadian Self-Sufficiency Project.’ SRDC Working Paper 03-05

Li, Q. (1996) ‘Nonparametric testing of closeness between two unknown distributions.’ *Econometric Reviews* 15, 261–274

Mortensen, D.T. (1977) ‘Unemplyment insurance and job search decisions.’ *Industrial and Labor Relations Review* 30(4), 505–517

Postel-Vinay, F., and J.-M. Robin (2002) ‘Equilibrium wage dsipersion with worker and employer heterogeneity.’ *Econometrica* 70(6), 2295–2350

Stern, S., and J. Canals-Cerda (2002) ‘Empirical search models.’ In *Search Theory and Unemployment,* ed. Steven Woodbury and Carl Davidson (Kluwer Academic Publications)

Train, Kenneth (2003) *Discrete Choice Methods with Simulation* (Cambridge University Press)

Wolpin, Kenneth, and Zvi Eckstein (1989) 'The specification and estimation of dynamic stochastic discrete choice models: A survey.' *The Journal of Human Resources* 24, 562–598

Zabel, Jeffrey, Saul Schwartz, and Stephen Donald (2004) 'An econometric analysis of the impact of the Self-Sufficiency Project on unemployment and employment durations.' SRDC Working Paper 04-05

Table 4: Participation equation: Demographic variables

Variables	Model 1		Model 2		Model 3	
	Para.	**S.d.**	**Para.**	**S.d.**	**Para.**	**S.d.**
Intercept	-1.748	(0.166)⋆	-2.067	(0.170)⋆	-2.274	(0.095)⋆
Less than high school	-0.292	(0.039)⋆	-0.234	(0.042)⋆	-0.181	(0.035)⋆
Post-secondary	-0.016	(0.027)	-0.008	(0.030)	-0.038	(0.025)
University	0.064	(0.047)	0.053	(0.049)	-0.112	(0.035)⋆
Experience	4.926	(0.328)⋆	4.432	(0.346)⋆	4.708	(0.189)⋆
Age	-3.281	(0.345)⋆	-2.839	(0.360)⋆	-2.010	(0.216)⋆
Car	0.125	(0.012)⋆	0.098	(0.013)⋆	0.075	(0.012)⋆
Home	0.042	(0.010)⋆	0.050	(0.010)⋆	0.063	(0.009)⋆
Children less that 7 years	-0.216	(0.012)⋆	-0.202	(0.013)⋆	-0.214	(0.011)⋆
Children 7-18 years	-0.085	(0.010)⋆	-0.086	(0.011)⋆	-0.094	(0.009)⋆
Married	0.152	(0.019)⋆	0.134	(0.019)⋆	0.140	(0.018)⋆
Born in Canada (yes = 1)	0.102	(0.048)⋆	0.096	(0.051)⋆⋆	-0.066	(0.026)⋆
Gender (woman = 1)	-0.010	(0.082)	-0.003	(0.080)	0.044	(0.037)
Spring	0.082	(0.020)⋆	0.089	(0.020)⋆	0.084	(0.020)⋆
Summer	0.112	(0.018)⋆	0.123	(0.018)⋆	0.118	(0.018)⋆
Fall	0.162	(0.021)⋆	0.187	(0.021)⋆	0.180	(0.021)⋆
1994	-0.782	(0.027)⋆	-0.925	(0.026)⋆	-0.924	(0.025)⋆
1995	-0.451	(0.021)⋆	-0.619	(0.020)⋆	-0.618	(0.019)⋆
1997	0.234	(0.021)⋆	0.288	(0.018)⋆	0.271	(0.018)⋆
1998	0.432	(0.022)⋆	0.441	(0.020)⋆	0.414	(0.020)⋆
1999	0.519	(0.023)⋆	0.544	(0.022)⋆	0.504	(0.021)⋆
2000–2001	0.653	(0.031)⋆	0.694	(0.030)⋆	0.645	(0.027)⋆
Lag (work)	3.105	(0.013)⋆	3.059	(0.013)⋆	3.058	(0.013)⋆

⋆ Significant at 0.05 level.

Table 5: Participation equation: Treatment effects

Variables	**Model 1**		**Model 2**		**Model 3**	
	Para.	**S.d.**	**Para.**	**S.d.**	**Para.**	**S.d.**
Group variables						
Eligible	—		-0.938	(0.067)⋆	-1.107	(0.062)⋆
Unqualified×Months 25-36	—		-0.283	(0.074)⋆	-0.432	(0.063)⋆
Unqualified×Months 37-48	—		-0.182	(0.066)⋆	-0.320	(0.052)⋆
Unqualified×Months 49-60	—		0.026	(0.070)	-0.106	(0.066)
Unqualified×Months 61-72	—		0.058	(0.068)	-0.089	(0.057)
SSP	—		1.186	(0.042)⋆	0.976	(0.028)⋆
PostSSP	—		1.067	(0.060)⋆	0.860	(0.053)⋆
PostSSP× Trend	—		-0.027	(0.004)⋆	-0.026	(0.004)⋆
Ineligible×Month 2-12	—		1.162	(0.045)⋆	1.073	(0.036)⋆
Ineligible×Month 13-24	—		0.798	(0.044)⋆	0.705	(0.034)⋆
Ineligible×Month 25-36	—		0.619	(0.043)⋆	0.514	(0.034)⋆
Ineligible×Month 37-48	—		0.472	(0.048)⋆	0.381	(0.039)⋆
Ineligible×Month 49-60	—		0.353	(0.046)⋆	0.278	(0.036)⋆
Ineligible×Month 61-72	—		0.305	(0.048)⋆	0.230	(0.039)⋆
Monthly dummies						
Eligibility phase						
Months 2-4	-0.259	(0.063)⋆	—		—	
Months 5-8	-0.221	(0.056)⋆	—		—	
Months 9-12	-0.157	(0.053)⋆	—		—	
Qualification phase						
Months 13-16	-0.129	(0.054)⋆	—		—	
Months 17-20	0.181	(0.052)⋆	—		—	
Months 21-24	0.263	(0.053)⋆	—		—	
SSP phase						
Months 25-28	0.403	(0.054)⋆	—		—	
Months 29-32	0.485	(0.056)⋆	—		—	
Months 33-36	0.413	(0.057)⋆	—		—	
Months 37-40	0.257	(0.058)⋆	—		—	
Months 41-44	0.357	(0.057)⋆	—		—	
Months 45-48	0.175	(0.057)⋆	—		—	
Months 49-52	0.088	(0.057)	—		—	
Months 53-56	0.180	(0.060)⋆	—		—	
Months 57-60	0.101	(0.061)⋆⋆	—		—	
Post-SSP phase						
Months 61-64	0.061	(0.059)	—		—	
Months 65-68	0.026	(0.060)	—		—	
Months 69-72	-0.027	(0.059)	—		—	

⋆ Significant at 0.05 level.

Table 6: Participation equation: marginal treatment effects

Variables	Model 1	Model 2	Model 3
Group variables			
Eligible	—	-0.010	-0.028
Unqualified×Months 25-36	—	-0.012	-0.027
Unqualified×Months 37-48	—	-0.013	-0.029
Unqualified×Months 49-60	—	0.003	-0.012
Unqualified×Months 61-72	—	0.006	-0.011
SSP	—	0.139	0.110
PostSSP	—	0.088	0.067
Ineligible×Month 2-12	—	0.103	0.089
Ineligible×Month 13-24	—	0.110	0.094
Ineligible×Month 25-36	—	0.088	0.074
Ineligible×Month 37-48	—	0.068	0.056
Ineligible×Month 49-60	—	0.050	0.040
Ineligible×Month 61-72	—	0.043	0.034
Monthly dummies			
Eligibility phase			
Months 2-4	-0.016	—	—
Months 5-8	-0.017	—	—
Months 9-12	-0.014	—	—
Qualification phase			
Months 13-16	-0.013	—	—
Months 17-20	0.021	—	—
Months 21-24	0.033	—	—
SSP phase			
Months 25-28	0.054	—	—
Months 29-32	0.067	—	—
Months 33-36	0.057	—	—
Months 37-40	0.036	—	—
Months 41-44	0.048	—	—
Months 45-48	0.024	—	—
Months 49-52	0.012	—	—
Months 53-56	0.025	—	—
Months 57-60	0.014	—	—
Post-SSP phase			
Months 61-64	0.008	—	—
Months 65-68	0.004	—	—
Months 69-72	-0.004	—	—

Marginal effects are computed as means over corresponding phase.

Table 7: Wage equation

Variables	Model 1		Model 2		Model 3	
	Para.	**S.d.**	**Para.**	**S.d.**	**Para.**	**S.d.**
Intercept	—		—		1.577	(0.003)*
Less than high school	—		—		0.017	(0.005)*
Post-secondary	—		—		0.044	(0.003)*
University	—		—		0.096	(0.004)*
Experience	—		—		3.304	(0.018)*
Experience^2	—		—		-0.642	(0.034)*
Exper.×LHS	—		—		0.047	(0.024)*
Exper.×PostSec	—		—		-0.159	(0.014)*
Exper.×Univ	—		—		-0.192	(0.018)*
Unqualified×Months 25-36	—		—		-0.093	(0.009)*
Unqualified×Months 37-48	—		—		-0.073	(0.007)*
Unqualified×Months 49-60	—		—		-0.113	(0.007)*
Unqualified×Months 61-72	—		—		-0.144	(0.006)*
SSP	—		—		-0.027	(0.003)*
PostSSP	—		—		0.007	(0.003)*
PostSSP (trend)	—		—		0.001	(0.000)*
Ineligible×Month 2-12	—		—		0.001	(0.002)
Ineligible×Month 13-24	—		—		-0.013	(0.002)*
Ineligible×Month 25-36	—		—		0.003	(0.002)
Ineligible×Month 37-48	—		—		0.013	(0.002)*
Ineligible×Month 49-60	—		—		0.024	(0.002)*
Ineligible×Month 61-72	—		—		0.008	(0.002)*

⋆ Significant at 0.05 level.

Table 8: Covariance matrix

Variables	**Model 1**	**Model 2**	**Model 3**			
	Para.	**S.d.**	**Para.**	**S.d.**	**Para.**	**S.d.**
CHOLESKY PARAMETERS						
C00					-0.099	(0.000)*
C01					-0.016	(0.002)*
K00					0.593	(0.001)*
K01					0.381	(0.010)*
K11					-0.770	(0.010)*
VARIANCE PARAMETERS						
σ_ξ					0.010	
$\sigma_{\zeta\xi}$					0.002	
σ_ζ					1.000	
σ_α	0.699	(0.013)*	0.746	(0.015)*	0.352	
σ_η					0.226	
$\sigma_{\alpha\eta}$					0.737	

* Significant at 0.05 level.

Note that $C = \begin{pmatrix} C00 & 0 \\ C01 & 1 \end{pmatrix}$, $K = \begin{pmatrix} K00 & 0 \\ K01 & K11 \end{pmatrix}$ so that

$CC' = \begin{pmatrix} \sigma_\xi & \sigma_{\xi\zeta} \\ \sigma_{\xi\zeta} & 1 \end{pmatrix}$ and $KK' = \begin{pmatrix} \sigma_\eta & \sigma_{\eta\alpha} \\ \sigma_{\eta\alpha} & \sigma_\alpha \end{pmatrix}$