An Endogenous Search Model and its Applications

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Abstract

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The existing literature on empirical job search models concentrates on studying the effects of unemployment insurance (UI) benefits, and the primary interest has been in male displaced workers. It is usually assumed that displaced workers start to search for new jobs immediately after the separation, treating the labor force participation decision of the displaced workers as an exogenous issue.

This thesis proposes a job search model where the participation decision of the displaced workers is made endogenous. The introduction of participation data enables us to identify more parameters and to avoid potential selection bias in the empirical work. The model is applied to study how the presence of young children affects the reservation wage and the escape rate from unemployment of female workers, and the gender wage gap between male and female workers. By its empirical work, the thesis tries to broaden the range of application of the job search theory.

The empirical results of the thesis are based on a panel of young Canadians who suffered a permanent job displacement. It is found that the offer arrival rate is the primary channel through which child status may affect the reservation wage of female workers, while child care cost differentials between the states of employment and unemployment may play only a minor role. It is also found that the effects of child status on male workers are much smaller than that on female workers with respect to the reservation wage, the offer arrival rate and the escape rate from unemployment. This suggests that the presence of young children in a worker's family contributes an important part to the gender wage gap.

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Chapter 1

Introduction and Literature Review

1.1 The Search Model

A worker displaced from his or her job needs to reassess the current economic environment and makes a decision whether to look for a new job or to drop out of the labor force. If the best choice is to engage in looking for another job, the worker has to evaluate an offer when it is received and decide whether to accept the offer or search for another one. In each time period in the process, all the potential choices must be based on the worker's expectations about the future. The forward looking attitude of each individual worker, the time dimension, and the incompleteness of market information, leave the individual facing uncertainty on all possible choices.

Therefore, in modelling the behavior of a job seeker, economists must take the intertemporal nature of the decision making process into consideration. Job search theory, pioneered by Stigler (1961, 1962) and McCall (1965) and subsequently advanced by a number of economists, is built to accommodate this uncertain situation. Since the early 1970s, the theory has been developed into a very rich literature.[1] The basic tool of job search theory is dynamic programming, and the optimal solution of

[1] In Devine and Kiefer (1991), more than 600 empirical studies have been documented within the search framework.

the search problem is characterized by the reservation wage policy, which is a criterion that balances the marginal cost and the expected marginal benefit of searching for an additional offer. The reservation wage equation is also referred to as the optimality condition. If the offered wage rate is above the reservation wage, the job seeker will accept it and then move from the unemployment state to the employment state. But if the wage rate is below the criterion, the worker will reject the offer and continue the searching process (or withdraw from the labor force if the non-participation state is taken into consideration).

Job search theory offers insights into a number of economic phenomena. Among others, we see that,

1. The unemployment state can be a productive one for a job seeker. The time spent searching for job offers may be viewed as an investment in the worker's human capital that improves his or her position in the labor market. The investment is usually expected to transform into a higher re-employment wage rate.

2. The unemployment state and the search process are costly, and the cost of being unemployed and the cost of searching will affect one's reservation wage. Other things being equal, anything that reduces search costs tends to raise the reservation wage of the job seeker, and vice versa.

3. Given the offer arrival rate and the distribution of job offers, the reservation wage of an individual job seeker determines the expected unemployment duration of the individual. In other words, the reservation wage itself effectively sets up the optimal "stopping rule" for the unemployed worker who searches for a new job.

Hence, it is important to study the mechanism that determines a job seeker's reservation wage in order to understand the labor market behavior of displaced. workers. For example, it is interesting to see whether the reservation wage of a job seeker is constant, decreasing or increasing over time, and what factors affect the difference between the reservation wages of different labor market groups.

1.2 Early Empirical Work

It is interesting to observe that the implications of the theoretical search model had not been tested empirically until the mid 1970s. Early empirical work concentrated on studying the relationship between unemployment insurance (UI) benefit provision and job search behavior of the unemployed workers (see Atkinson and Micklewright (1991) for a review).

Early empirical works approach the problem primarily by simple linear or log-linear regression models of wage data and/or unemployment duration data. For example, in their well known work, Ehrenberg and Oaxaca (1976) regress the logarithm of weeks of nonemployment and the logarithm of re-employment wage on the replacement rate and a number of other regressors that capture the heterogeneity of individual reservation wage for different age and gender groups. Evidence found suggests that the level of the UI benefit, the duration of the UI benefit, and the replacement rate are all negatively related to the duration of unemployment. The replacement ratio of UI benefits strongly prolong unemployment durations, though the magnitude of the effect of UI benefit on the length of unemployment is largely unsettled. On the other hand, the effect of UI benefit on the re-employment wage rates is somewhat mixed for different individual groups. For example, with respect to the effect on re-employment wage, Ehrenberg and Oaxaca (1976) found that postunemployment wages of older workers increase slightly with benefit levels, while the effect is negligible for all other groups. On the other hand, Classen (1977, 1979) found no UI benefits effect on the re-employment wage in his studies.

It is widely recognized that these early studies represent an important effort to test the job search theory empirically, though the basic idea of the job search theory is only loosely linked with the empirical models. Methodologically, the major drawback of those studies is that the statistical methods employed are inappropriate. Notably, the censoring of unemployment duration data and selection bias problems are not correctly addressed. As a result, the interpretation of the empirical results in those studies is invalid. Recognizing the shortcomings of the early work, subsequent studies pay more attention to the underlying stochastic processes that generate the data in developing the empirical models.

1.3 Empirical Work along the Reduced Form Approach

It should be noticed that one can easily deduce the distributions of accepted wage data and unemployment duration spells, given proper assumptions of the theoretical search model. For example, in a stationary search model, the unemployment spell duration would follow an exponential distribution if the offer arrival rate is constant, and the accepted wage distribution is simply the truncated part of the wage distribution from which the offers are drawn.[2] In the empirical search literature, studies that do not impose the optimality condition of job search are referred to as the reduced form models, while studies which do implement the optimality condition are referred to as structural models. The former often concentrate on duration data while the latter employ both accepted wage data and unemployment duration data.

A very large number of papers are devoted to the study of the unemployment duration data without implementing the reservation wage policy.[3] On the one hand, the implementation of a reduced form model does not require information on the behavior of the reservation wages (which is usually not observable). On the other hand, given the fact that the measurements of the underlying random variables faced by economists are similar to those faced by biostatisticians (the time until an event occurs), the well developed biostatistics framework[4] makes it easy for economists to accommodate the special feature of the unemployment duration data, e.g. right censoring. Economists have to deal with some additional issues that biostatisticians do not need to face. These arise as a consequence of differences in sampling structures. In particular, randomized experiments are rare in economics. A sample obtained can

[2]The accepted wage distribution is bounded (from the left) by the reservation wage.

[3]For example, among the 600 studies reviewed in Devine and Kiefer (1991), only a small number of them are classified as structural models.

[4]Two notable works on this subject are Kalbfleisch and Prentice (1980), and Cox and Oakes (1984)

hardly be viewed as a draw from a homogenous population, and hence observed, as well as unobserved, heterogeneity have to be carefully addressed by economists.

The reduced form studies carry on the early empirical work with respect to the effect of UI benefits on unemployment duration by analyzing the hazard function. The hazard function can be viewed as the instantaneous rate of leaving one state for another at a point of time. Compared to the probability distribution function, it carries the same information for the random variable in question, but usually has a much simpler structure.[5] Lancaster (1979) and Nickel (1979) introduce Cox's (1972) proportional hazard model into the study of unemployment duration data. The model enables them to handle observed and unobserved heterogeneity issues. Parametric estimation became the norm following their work (see Atkinson, Gomulka, Micklewright, and Rau (1984), Solon (1985), Podgursky and Swaim (1987), Ham and Rea (1987)), although there are a number of authors who have discussed non-parametric maximum likelihood estimation (e.g., Heckman and Singer (1984), Moffitt (1985)) and semi-parametric estimation (see Han and Hausman (1990), Sueyoshi (1992), and Meyer (1990)).

The reduced form studies are diversified in model specification, the ways they treat unobserved heterogeneity, and various measurement issues. The evidence found varies greatly. Perhaps for this reason, methodological discussions in these studies have often motivated subsequent research.

1.4 Empirical Work along the Structural Approach

The central result of the search theory is the reservation wage. To incorporate the reservation wage strategy into empirical work, researchers need one of the following:

[5] More precisely, let T be the duration of stay in a state, then the hazard function of the continuous random variable T can be defined as $\theta(t) = \lim_{dt \to 0} \frac{P(t \le T < t+dt | T \ge t)}{dt}$. Hence, $\theta(t) = \frac{f(t)}{1-F(t)}$, where $f(t)$ and $F(t)$ denote the probability density and the cumulative distribution functions, respectively. $\overline{F}(t) = 1 - F(t)$ is often referred to as the survivor function.

- Direct observations on the reservation wages of individual job seekers. This is often based on answers to the question "what is your minimum acceptable wage rate?" in a survey.

- Some sort of approximation to the reservation wage. Examples include the official minimum wage rate by region (or industry) depending on where the sample was drawn, the minimum wage of the sample, even the previous wage rate.

- One may also seek an approximate, or even an exact solution, to the reservation wage equation.

With direct observations, a small number of authors have analyzed the behavior of the reservation wage over the spell of unemployment and the effect of UI benefit provisions on the reservation wage and unemployment duration. Structural studies start with a piece of work by Lancaster and Chesher (1983) in which no estimation was conducted. Instead, they calculate the elasticities of the reservation wage and expected unemployment duration with respect to the UI benefit and the offer arrival rate. Ridder and Gorter (1988) estimate the structural parameters with an approximation of the reservation wage equation, while van den Berg (1990a) addresses the nonstationarity problem of the reservation wage. Empirical results of these works are in general consistent with some predictions of the theoretical search model. But it should be noticed that there exist certain inconsistencies in the data on reservation wages and expected wage rates. For example, in the sample studied by Jones (1988), about 25% of the respondents reported reservation wages that are above their expected wage rates.[6] It seems that the design of questionaires and the respondents' ability to interpret the questions asked make studies along this line problematic.

Given the assumptions of the search model, if one has observations on unemployment durations and accepted wages, the joint density and hence the likelihood function of the data are straightforward. However, estimation must be subject to the condition that accepted wages must exceed the reservation wages. If one assumes

[6] In an early work, Stephenson (1976) also found the same problem.

that the sample is drawn from a homogeneous population with a constant reservation wage, then the implied maximum-likelihood estimates for the reservation wage would be the sample minimum. Using this estimate, the other structural parameters can be obtained easily. Flinn and Heckman (1982) explore the idea and develop a non-parametric maximum-likelihood estimation procedure.

Without access to reservation wage data, another way of estimating the structural parameters of the search model is to find an approximate solution to the optimality condition and subsequently implement the approximation into the empirical model. Kiefer and Neumann (1979) follow this approach. They assume that the logarithm of wage offers are drawn independently from normal distributions, and are linear in the characteristics of individuals, so that the logarithms of the unobserved reservation wages are also linear. Given the theoretical restriction of search theory that accepted wages must exceed the reservation wages, the employment condition becomes a standard Probit model. Following a standard two-step estimation strategy, Kiefer and Neumann use consistent estimates of the Probit model, applying generalized least squares estimation to the accepted wage equation to obtain the structural parameters. Kiefer and Neumann (1981) extend their previous work by incorporating unobserved heterogeneity into their model directly. With additional data on search intensity and the offer arrival process, Blau and Robins (1986) extend the Kiefer and Neumann approach. A key assumption adopted by the latter authors is that the offer arrival rate is one per period. As Flinn and Heckman (1982) point out, without such an assumption, Kiefer and Neumann would be unable to identify the structural parameters.

Instead of finding an approximate solution to the optimality equation, Narendranathan and Nickell (1985) introduce an approximation to the reservation wage equation itself, and determine the exact solution to the approximation of the optimality equation. The authors do not have appropriate observations on accepted wages, so they construct data by fitting least squares regressions to previous wage data and then use numerical methods to construct the reservation wage for each individual. The structural parameters are then obtained by maximizing the likelihood function based on unemployment duration data, the constructed reservation wage and accepted wage data. Another study along these lines is conducted by van den Berg (1990b). The difference is that this model allows unemployed workers to leave for either the employment or the nonparticipation states. However, the expected utility flows in the unemployment and the nonparticipation states are assumed to be identical and equal to a constant, which enables him to find the solution of the approximation to the reservation wage equation.

The findings in these studies, with respect to the effects of UI benefits on reservation wages and unemployment durations, are close to each other. These studies are also consistent in signs with the results based on direct observations of reservation wage data, though not in magnitudes. In general, these effects are found to be relatively small. The acceptance probability estimated is high, implying that the offer arrival rate plays an important role in affecting the duration of unemployment. The less impressive part of these works is that the empirical models fit poorly.

Different from all the work mentioned above, Wolpin (1987) tries to find an exact solution to the optimality equation for the reservation wage. A measurement error is introduced for accepted wages.[7] He models the transition process of high-school graduates from unemployment to employment, assuming a finite search horizon. All the theoretical implications of the search model are imposed into the econometric specification. Unfortunately, Wolpin's estimation results are extremely sensitive to the specification of the offer distribution. His estimates associated with normally distributed wage offers are not reported, and the estimates associated with log normal job offers are, at best, mixed. Overall, in the presence of nonstationarity, and without direct observations on the reservation wage, Wolpin's work represents the first effort to fully implement theoretical restrictions into empirical work.

[7] Wolpin's work is quite ambitious. He intends to estimate all the structural parameters in addition to the subject discount rate. The introduction of the measurement error in the accepted wages helps him to identify all the structural parameters in his model. One should note that this will likely raise the sensitivity of the estimates to the model specifications.

1.5 The Plan of the Thesis

Recent empirical studies of job search develop in a few directions.[8] This thesis proposes an endogenous search model where the participation decisions of the displaced workers are taken into consideration. Since the non-participation state is studied along with the employment and unemployment state, the model can be also referred to as a three-state search model. The study will follow the structural approach. With the exact solution to the reservation wage equation imposed on the econometric model, estimation of the structural parameters in the reservation wage equation is attempted. This allows one to characterize the behavior of reservation wages. The thesis goes beyond the study of UI benefit effect on job search and extends the analysis to include the effect of child status on the behavior of displaced female workers, as well as the wage gender gap.

The idea of endogenous search is stimulated by household production theory (which dates back to the pioneering work of Becker (1965)), which recognizes the value of the time devoted to household activities by an individual. It is perfectly rational for a worker to withdraw from the labor force, if the value of searching, or the value of working, is below the value generated by home production. Flinn and Heckman (1983) appear to be the first to conduct a test of the hypothesis that the unemployment and the nonparticipation states are statistically different. Using a Gompertz hazard function and a sample of young white males, the null is rejected at the 5% significance level. Burdett et al. (1984), Mortensen and Neumann (1984), and Blau and Robins (1986) all model transition rates between the three labor market states based on a Markov process. The exception is that of van den Berg (1990b), as discussed above, who attempts to estimate the structural parameters using an approximation to the reservation wage equation. These works suggest, among other things, that the nonparticipation and the unemployment states should be treated differently.

The difference between this thesis and the studies reviewed above is evident.

[8]See Christensen and Kiefer (1994) for a different way of estimation, Bowlus et al. (1996) for an estimation of the equilibrium search model.

The distinguishing feature of this study is that it admits the endogenous nature of search decision. As noticed, the participation decision is usually treated as an exogenous issue and hence ignored by most empirical work (reduced form and structural studies). The model used here also allows other issues to be addressed in addition to the effect of UI benefit provision within a proper structural specification. For example, the costs of job searching and employment, the effect of household productivity on the reservation wage and the wage gender gap may also be studied.

Technically speaking, the model proposed in this thesis is somewhat close to the work of Wolpin (1987) and of van den Berg (1990b). Similar to the former, an exact solution to the reservation wage is also sought, but the current study seeks the solution within a three-state, instead of a two-state, labor market. While van den Berg (1990b) admits a three-state labor market, his solution is based on an approximation to the reservation wage equation, this thesis seeks an exact solution to the reservation wage equation itself. It is also evident that almost all the works in the literature concentrate on the effects of UI benefit provisions. An attempt is made here to study some other important policy issues.

The thesis is organized as follows. In Chapter 2, the theoretical search model that incorporates the non-participation state with the employment and unemployment states for the displaced workers is presented. Chapter 3 develops the econometric model for this search model, discusses estimation issues, and compares some empirical results with the previous structural studies. The effects of child care costs on female displaced workers and the wage gender gap are studied in Chapters 4 and 5. A summary and conclusions are contained in Chapter 6. The data sets employed in this study are presented in Chapter 7.

Chapter 2

The Theoretical Model of Endogenous Search

On a theoretical basis, the multi-state search model is a relatively straightforward extension of the simple search model. It can give us a more complete picture of the labor market dynamics. However, when one tries to confront the model with empirical issues, when one attempts to test the implications of the theory, data availability and computational costs of the model immediately show up. This is especially true in the case of empirical work that follows a structural approach.

The primary concern of this thesis is the labor market behavior of the displaced workers. We shall concentrate on studying the decision process of those workers after their displacement. The decision problems faced by those displaced workers are either to drop out from the labor force and engage in household activities, or to start searching for another job. If an individual worker decides to remain in the labor force, he or she will then face the choices between accepting and rejecting an offer.

This thesis proposes a stationary endogenous search model that can accurately describe a few aspects of the labor market dynamics of the displaced workers. In order to make the model empirically tractable, we make further assumptions in addition to those that are usually made in developing the standard search model.[1]

[1]See for example, Mortensen (1986).

2.1 The Assumptions of the Model

The theoretical search model proposed by this thesis is based on the following assumptions. As noted, some of them are standard ones, and are usually assumed in the literature, while others are specific to this study.

Assumption 1 Displaced workers make their search decisions immediately after the displacements. The workers will have to decide whether to search for new jobs or to withdraw from the labor force upon displacement and engage in household production.

Assumption 2 The displaced workers receive unemployment compensation at rate b in each period of unemployment if they decide to search for new jobs. In other words, only those who decide to search for new jobs are entitled to the UI benefit, those who decide to withdraw are not. The UI benefit is assumed to be constant over the spell of unemployment. For identification purpose, we normalize other sources of income to be 0 for all three labor market states.

Assumption 3 Displaced workers who decide to remain in the labor force will maximize their life time earnings, at the discount factor $\beta = \frac{1}{1+\rho}$ over an infinite time horizon, where ρ is the instantaneous interest rate, or the subject discount rate, with $0 < \beta < 1$, and $\rho > 0$.

Assumption 4 A job seeker receives at most one offer per period of time and job offers arrive independently. The probability that an offer arrives in a time period is constant and equal to δ. The time frame is discrete.

Assumption 5 A job offer is characterized by an hourly wage rate w and is assumed to be drawn independently from a distribution that is known by the job seekers. The distribution is well defined with finite mean and variance. In particular, the wage offer is assumed to follow an exponential distribution with distribution function $F(w) = 1 - \exp(-\lambda w)$, where λ is the parameter of the distribution.

Assumption 6 Once an offer is accepted, it will be held forever, and once an offer is rejected, it can not be recalled.

Assumption 7 Both the employed and unemployed states are costly to the worker. The costs of job search are assumed to be $\Gamma_u(K)$, and the costs of working are $\Gamma_e(k)$, where K is an exogenous variable, represents the child status of an individual. Initially, we shall assume that these costs are constants. They will be allowed to depend on child status latter.

Assumption 8 For a displaced worker who decides not to search for a new job, the value of non-market time is given by $\frac{1}{\tau_1}\exp(\tau_1 K)$, where K is the number of children, and τ_1 can be viewed as the productivity parameter of household activities.

Assumptions 2 through 6 are more or less standard in a stationary search model. Complete elaborations are provided by a number of authors.[2] Assumptions 2 and 5 are more important. Assumption 2 is crucial in generating a constant reservation wage policy, while assumption 5 enables an easy-to-apply optimality condition in empirical work.

Assumption 1 seems limited at first glance, but it is not unrealistic in practice. An advantage of this assumption is simplification. Under this assumption, displaced worker may opt for non-participation, unemployment with search, or employment. This effectively sets the transition rates from employment to non-participation, non-participation to employment, and non-participation to unemployment to be 0.

In the literature, search models typically absorb search costs into a constant together with any income, e.g. UI benefits, received when a worker is unemployed. This is usually termed the net cost of search (or net income when the term is positive) for the unemployed. Assumption 7 isolates search costs from income received by the unemployed workers. With respect to the costs of labor market activities, the model is different in that it allows the cost of working to be integrated into the decision environment. This seems quite reasonable in that workers do incur costs on their jobs. One type of working cost is child-care costs; another is some home-care costs as people who are working have to purchase a certain amount of home-care services from the home-service market. Such costs can be viewed as a reduction to the wage

[2]See, for example, Lippman and McCall (1976), Mortensen (1986).

rate, and they will naturally affect the reservation wages of the unemployed workers. Assumption 7 also makes it clear that the monetary cost is 0 for those who decide to withdraw from the labor force. This is justified in that one does not need to pay for drawing a value from the non-participation state, and once settled down in the non-participation state, one does not need to pay anything to anybody for staying in that state. For example, a displaced worker who withdraws from the labor force to engage in child rearing activity does not have to pay for child-care service (i.e. the worker can perform child-care privately), while those who are looking for a job, or who are actually working do need to pay for this service.

Assumption 8 effectively proposes the value function (without discount) for the nonparticipant. The functional form for the output of home production is chosen to accommodate two facts. On the one hand, some displaced workers do withdraw from the labor force for the sake of child care activities. This is particularly true for female displaced workers. The output of household activities for these workers will relate positively to the number of children.[3] On the other hand, not all workers who decide to drop out will engage in child-care activities; some of them do not have any children at the time of withdrawal (though they might have plan to have children in the future). The function makes the output of home activities being equal to $\frac{1}{\tau_1}$ when an individual does not have any children. We further add a term τ_1 to the output of household activities in order to avoid putting any restriction on the value of the parameter τ_1.

2.2 The Optimality Condition

Given the assumptions, the value functions for the three labor market states can be derived. Denoting E_0 as the mathematical expectation of future income Y_t, given information known at time $t = 0$, then, upon job separation, the decision problem faced by a worker is,

[3] K is an integer, but for illustrative purpose, take the derivative of the output function with respect to K. This gives us $\exp(\tau_1 K) > 0$. In other words, the sign of τ_1 does not affect the direction of the relationship between the number of children and the output of home production.

$$\text{Max} \quad E_0 \sum_{t=0}^{\infty} \beta^t Y_t.$$

$$\text{s.t.} \quad Y_t = \begin{cases} b - \Gamma_u(K) & \text{if unemployed;} \\ w - \Gamma_e(K) & \text{if employed;} \\ \frac{1}{\tau_1}\exp(\tau_1 K) & \text{if withdraw.} \end{cases}$$

Denoting a_1 as actions for the participation decision, with $a_1 = 1$ if the worker decides to search for another job, and $a_1 = 0$ if the worker decides to withdraw from the labor market. Denoting a_2 as actions when an offer is received by the participant, with $a_2 = 1$ if the worker accepts the offer, and $a_2 = 0$ otherwise. Then Bellman's equation for this problem becomes

$$V = \underset{\{a_1, a_2 \in (0,1)\}}{\text{Maximize}} \left\{ \begin{array}{c} (1-a_1)[\frac{1}{\tau_1}\exp(\tau_1 K)] + a_1[a_2(w - \Gamma_e(K)) \\ +(1-a_2)\,(b - \Gamma_u(K))] + \beta E[V|a_1, a_2] \end{array} \right\}.$$

Let $V_e(w)$ be the value function of accepting a job offer at wage rate w; $V(w')$, the value function of the offer w' that could be received in the next period of time; V_u the value function of unemployment with job search; and V_n, the value function of leaving the labor force and engaging in household production. The value functions for the labor market three states can be derived as,

$$V_e(w) = \frac{1}{1-\beta}(w - \Gamma_e(K)); \tag{2.1}$$

$$\begin{aligned} V_u &= b - \Gamma_u(K) + \beta\, E[V] \\ &= b - \Gamma_u(K) + \beta \int_0^{\infty} V(w')\, dF(w); \end{aligned} \tag{2.2}$$

$$V_n = \frac{1}{1-\beta}\left(\frac{1}{\tau_1}\exp(\tau_1 K)\right). \tag{2.3}$$

Consider first the decision problem of a displaced worker who has decided to search for another job; should an offer be received, and if the worker behaves optimally (as if the worker applies the Bellman's principle of optimality), the solution to the worker's problem has the following form,

$$V = \begin{cases} \frac{w-\Gamma_e(K)}{1-\beta} & \text{if } w \geq w^*; \\ \\ b - \Gamma_u(K) + \beta \int_0^\infty V(w')\, dF(w') = \frac{w^*-\Gamma_e(K)}{1-\beta} & \text{if } w < w^*; \end{cases}$$

where w^* is defined as the reservation wage of the job seeker. To see the definition for w^*, notice that the value of accepting an offer is an increasing function of w, and the value of continuing the search is a constant. Hence, an intersection point exists between the two value functions. At this point, the two values are equal, and the job seeker is indifferent between accepting or rejecting an offer; to the left of this point, the offer will be rejected, and to the right of this point, the offer will be accepted. Symbolically, w^* is a point such that,

$$\frac{w^* - \Gamma_e(K)}{1-\beta} = b - \Gamma_u(K) + \beta\ E[V].$$

Given that job offers arrive at rate δ, and offers are drawn from the distribution $F(w)$, the expected value of following the optimal decision rule is,

$$\begin{aligned} E[V] &= \delta \int_0^\infty V(w)\, dF(w) + (1-\delta)\, V_u \\ &= \delta F(w^*) \int_0^{w^*} \frac{V(w)f(w)}{F(w^*)} dw + \delta\,[1 - F(w^*)] \int_{w^*}^\infty \frac{V(w)f(w)}{1-F(w^*)} dw \\ &\quad +(1-\delta)(b - \Gamma_u(K) + \beta E[V]) \\ &= \delta\, F(w^*)\, E[V(w)|w < w^*] + \delta\,[1 - F(w^*)]\, E[V(w)|w \geq w^*] \\ &\quad +(1-\delta)(b - \Gamma_u(K) + \beta E[V]) \\ &= \delta\, F(w^*)[b - \Gamma_u(K) + \beta\, E(V)] + (1-\delta)(b - \Gamma_u(K) + \beta E[V]) \end{aligned}$$

$$+\delta\,[1-F(w^*)]\int_{w^*}^{\infty}\frac{w-\Gamma_e(K)}{1-\beta}\,\frac{f(w)}{1-F(w^*)}\,dw$$

$$= \delta\,F(w^*)[b-\Gamma_u(K)+\beta\,E(V)]+\delta\,[1-F(w^*)]\frac{E[w|w\geq w^*]}{1-\beta}$$

$$-\frac{\delta\,[1-F(w^*)]\Gamma_e(K)}{1-\beta}+(1-\delta)(b-\Gamma_u(K)+\beta E[V])$$

$$= \frac{1}{1-\beta}\Big\{\big[1-\delta(1-\delta(1-F(w^*))\big]-\Gamma_e(K)+\delta(1-F(w^*))E[w|w\geq w^*]\Big\}.$$

Given the constant offer arrival rate δ and the known offer distribution $F(w)$, the acceptance probability is defined as,

$$\pi = \Pr[w\geq w^*] = 1-F(w^*).$$

The product of the probability of an offer arriving and the probability of an offer being acceptable is defined as the escape rate from unemployment to employment. This is also referred to as the hazard rate of unemployment, measuring the instantaneous probability that an unemployed worker moves to the employment state during a time period,

$$\theta = \delta\pi.$$

Hence, the expected value of following the optimal policy can be written as

$$E[V] = \frac{1}{1-\beta}\{(1-\theta)\,w^*-\Gamma_e(K)+\theta\,E[w|w\geq w^*]\}. \tag{2.4}$$

Substituting equation (2.4) into equation (2.2) to obtain V_u,

$$V_u = b-\Gamma_u(K)+\frac{\beta}{1-\beta}\left[(1-\theta)\,w^*-\Gamma_e(K)+\theta\,E[w|w\geq w^*]\right].$$

Since at w^*,

$$V_u = V_e = \frac{w^*-\Gamma_e(K)}{1-\beta},$$

one may solve for w^* as,

$$w^* = \frac{1}{1-\beta(1-\theta)}[(1-\beta)(b+\Gamma(K)) + \beta\theta E[w|w \geq w^*]]. \quad (2.5)$$

Equation (2.5) is the reservation wage equation, also referred to as the "optimality condition" in the job search literature, where $\Gamma(K) = \Gamma_e(K) - \Gamma_u(K)$ represents the difference between the employment costs and the costs of job search.

Notice that equation (2.5) can also be written as,

$$w^* = b + \Gamma(K) + \frac{\beta\theta}{1-\beta}[E(w|w \geq w^*) - w^*]]. \quad (2.6)$$

Applying the Leibniz rule to Equation (2.6), we obtain the derivative $\beta(1-\theta)$, hence, there exists an operator $T : w^* \longrightarrow w^*$ that is a contraction mapping of modulus $0 < \beta < 1$, and hence, w^* is uniquely determined.[4]

Given equation (2.4), the value function of searching can be further written as,

$$V_u = b - \Gamma_u(K) + \frac{\beta}{1-\beta}[(1-\theta)w^* - \Gamma_e(K) + \theta E[w|w \geq w^*]. \quad (2.7)$$

Comparing equations (2.7) and (2.3), it is clear that the necessary condition for a displaced worker to withdraw from the labor force, is,

$$\frac{1}{1-\beta}(\frac{\exp(\tau_1 K)}{\tau_1}) \geq b - \Gamma_u(K) + \frac{\beta}{1-\beta}[(1-\theta)w^* - \Gamma_e(K) + \theta E[w|w \geq w^*]], \quad (2.8)$$

where w^* is given by equation (2.5). Of course, if we change the direction of the inequality of (2.8), we can also obtain the necessary condition for a displaced worker to search for another job. In other words, equation (2.8) is both the necessary and the sufficient condition for a displaced worker who needs to make a choice between participation and withdrawal.

[4]See Stokey and Lucas(1989) for the proof.

2.3 The Properties of the Model

Clearly, the model is subject to the restrictions implied by a standard search model as quite a number of the assumptions made in the standard model are maintained in the framework of this thesis. Differentiating equation (2.6) with respect to the UI benefit b, the discount rate $\rho = \frac{1-\beta}{\beta}$, and the arrival rate δ, we obtain the following results:

$$\begin{aligned}
\frac{\partial w^*}{\partial b} &= \frac{\rho}{\rho+\theta} \in (0,1); \\
\frac{\partial w^*}{\partial \delta} &= \frac{\pi}{\rho+\theta}[E(w|w \geq w^*) - w^*] > 0; \\
\frac{\partial w^*}{\partial \rho} &= -\frac{\theta}{\rho}\frac{E(w|w \geq w^*) - w^*}{\rho+\theta} < 0; \\
\frac{\partial w^*}{\partial K} &= \frac{\rho}{\rho+\theta}\Gamma(K).
\end{aligned}$$

Hence, the reservation wage is positively related to the UI benefit and the offer arrival rate, and negatively related to the discount rate. The effect of child status K [5] on the reservation wage depends on the sign of $\Gamma(K)$, which can be either positive, negative or zero. This will be further discussed latter. Other derivative restrictions such as the escape rate of unemployment with respect to the UI benefit and the discount rate, the expected wage with respect to the UI benefit, the discount rate, and the offer arrival rate can also be easily derived.

Given that the offer arrival rate is constant over the unemployment spell and the offer distribution is independent of the duration of unemployment, the escape rate from unemployment for a displaced worker who decides to search is a constant

[5] K is typically a discrete variable, the derivative here is for illustrative purpose.

$\theta = \delta[1 - F(w^*)]$. That is, the theoretical model also implies that the spell of unemployment duration follows the exponential distribution with parameter θ. Moreover, the density function for a completed spell of unemployment duration T is,

$$f(t) = \delta[1 - F(w^*)]\exp(-\delta[1 - F(w^*)]\,t).$$

In addition to the above restrictions, the model makes it possible to compare the costs of employment and job search. The parameter $\Gamma(K)$ represents the difference between employment costs and costs of job search. The introduction of a labor market cost differential is one of the contributions made by this thesis to the search theory. It allows one to address, within the search framework, the effects of employment costs and job search costs on a worker's participation decision, reservation wage, and unemployment duration. It also makes the empirical work more flexible. One may treat employment costs and costs of job search, and hence, the labor market cost differential as constants. As a constant, it can be either negative, positive or zero. A positive cost differential implies that employment costs are higher than search costs. In this case, a worker's labor force participation is discouraged; the worker's reservation wage will be raised, and his/her unemployment duration will be lengthened. On the other hand, if $\Gamma(K) < 0$, a displaced worker will be more likely to search for a new job instead of withdrawing from the labor force, his/her reservation wage will be reduced, and unemployment duration will be shortened. The possible asymmetry of the labor market costs has some clear policy implications, but as a hypothesis, to our knowledge, has never been tested.

When the costs across the employment and unemployment states are equal, i.e. if $\Gamma(K) = 0$, the optimality condition becomes,

$$w^* = b + \frac{\beta\delta\pi}{1-\beta}\big[E(w|w \geq w^*) - w^*\big].$$

This is the symmetric case in which the reservation wage will not be affected by the cost of job search and the cost of employment.

Of course, if the costs associated with the employment and the unemployment states are constant, it is not necessary to study the two costs separately. One of them may be normalized to 0 without any loss of generality. On the other hand, since this thesis also intends to study how child status may affect employment and search costs differently, these costs will be parameterized as functions of a number of independent variables in due course, the two costs are listed separately here.

The effect of the cost differential on the participation decision of a displaced worker can be seen from equation (2.8). Other things being equal, lower search costs will encourage a displaced worker to search for a new job and hence prevent labor force withdrawal. On the other hand, the cost differential affects the acceptance probability, which in turn affects the participation decision. Thus the cost differential affects the participation decision indirectly, though the direction of this indirect effect depends on the sign of the cost differential. Likewise, all other structural parameters that enter the reservation wage equation will affect the participation decision. Moreover, one can solve for K, the number of children, from the inequality, and determine the threshold level of children at which job search becomes unproductive for given structural parameters. In particular, we can express the threshold as,

$$K^{*} \geq \frac{1}{\tau_1} \log \left[(w^{*} - \Gamma_e(K^{*}))\tau_1 \right].$$

2.4 Concluding Remarks

The endogenous search model to be applied in this thesis has been derived in this chapter. The model encompasses all the aspects of the labor market behavior of the displaced workers as does the standard search model. In addition, the model used here has a number of new features.

Different from the traditional model where the decision to search is typically ignored, it takes the participation decision of the displaced workers into consideration and hence treats the participation decision of the displaced workers as endogenous.

Almost all of the studies which follow the structural approach assume the search decision exogenous, implying that displaced workers immediately search for another job. This is often a reasonable assumption for male displaced workers (as most structural models study the labor market behavior of the male displaced workers), but it may not be the case for female displaced workers who, for example, might have given birth prior to the displacement, or have heavy home care responsibilities. Upon their discharge from work, female workers' participation decision may not be as simple as their male counterparts. The endogenous nature of the participation decision might also be true for some male displaced workers.[6]

The model also admits the state dependency of the labor market costs, and is thus able to address the asymmetry of the relevant costs. State dependency may be an important factor since job search is typically less time consuming compared to employment (particularly full time employment). Displaced workers who are looking for jobs may be able to devote some of their time to household activities, which they would not be able to do once re-employed. The possible cost reduction of unemployment makes the expected net value of unemployment increasing and the net value of employment decreasing. Therefore, the cost differential in the reservation wage equation is expected to be positive, which means that the reservation wage (and the duration of unemployment spells) for those who decide to search for new jobs are higher.

The model is more flexible and more general than the standard search model. It allows one to see how the introduction of the participation decision may affect estimates on some key structural parameters.[7] If one specifies the cost of job search and the cost of working as a function of the number of children, one can address how child care costs may affect the labor market behavior of the displaced workers. Other specifications are also possible, enabling researchers to investigate the effects of these variables on the reservation wages, which may be of interest to the labor

[6]Another advantage of admitting the endogenousness of the participation decision is related to the estimation of the structural model. We shall discuss this in Chapter 4.

[7]Details are presented in Chapter 3.

market policy makers.[8] The model also allows us to address how the non-market time productivity can affect the wage gender gap using a structural approach in the search framework.[9]

[8]For more details, see Chapter 4.

[9]This is addressed in Chapter 5.

Chapter 3

The Econometric Model and its Estimation

This chapter specifies the econometric model for the three-state search model and presents the estimation strategy employed to implement the theoretical model. The offer distribution to be used is the exponential distribution, one of distributions that satisfies the recoverability condition established in Flinn and Heckman (1982). Naturally, one would like to see what will happen to the structural parameters if we take the displaced workers' participation decision as endogenous. Hence, comparisons between the estimates of the two- and the three-state models will be made.

3.1 The Econometric Model

As noted in Chapter 1, previous structural studies typically work with duration and wage data, and treat the participation decision of the displaced workers as exogenous. A potential problem here is that selection bias may be introduced. This study makes use of sample information concerning willingness to search reported by the displaced workers. In order to take into account individual unobserved heterogeneity in the value function of household production, a stochastic element α is introduced into the value function of the non-market time. α is assumed to be normally distributed as follows:

$$\alpha \sim N(0,\ \sigma^2). \tag{3.1}$$

In this specification, it can be seen that the following structural parameters are identifiable: λ (the wage distribution location parameter), δ (offer arrival rate), Γ_u(cost of search),[1] ρ or β (discount rate or discount factor),[2] τ_1 (home productivity) and σ (unobserved heterogeneity in the value of non-market time).

Defining a binary variable s_i =1 for those displaced workers who decide to search for new jobs, and s_i=0 for those who decide to drop out of the labor market and using the participation condition summarized in equation (2.8), the participation Probit of a worker can be written out. The probability that an individual i will search is

$$Pr\,(s_i = 1) = Pr[V_n \le V_u] = Pr[\alpha \le h(w_i^*)] = \Phi\left[\frac{h(w_i^*)}{\sigma}\right],$$

where,

$$h(w_i^*) = w_i^* - \frac{1}{\tau_1}\exp(\tau_1 K), \tag{3.2}$$

$\Phi(.)$ denotes the standard normal distribution function and w_i^* is given by the optimality condition (2.5). Then, the probability that an individual will drop out is,

$$Pr(s_i = 0) = Pr[V_n > V_u] = Pr[\alpha > h(w_i^*)] = 1 - \Phi\left[\frac{h(w_i^*)}{\sigma}\right].$$

Hence, the contribution to the likelihood function made by an individual's participation decision is,

$$\left\{\Phi\left[\frac{h(w_i^*)}{\sigma}\right]\right\}^{s_i}\left\{1 - \Phi\left[\frac{h(w_i^*)}{\sigma}\right]\right\}^{(1-s_i)}. \tag{3.3}$$

For those displaced workers who decide to search for new jobs, it is possible that, at the end of the survey, they are still searching and unemployed. For this group of workers, the unemployment duration data are censored, we observe incomplete

[1]Cost of employment is normalized to 0 in this chapter to facilitate estimation.

[2]The discount rate, or the discount factor, is typically assumed to be equal to a known constant in empirical search work.

duration spells t_i, and no accepted wage data are observable. On the other hand, for those who are re-employed, we can observe their accepted wage w_i and the lengths of their unemployment spell t_i. Defining a binary variable d_i, such that d_i=1 if we have complete observations on wage and duration data, and d_i=0 otherwise, then the contribution to the likelihood function by a displaced worker who decides to search for a new job is,

$$\left\{[1-\delta(1-F(w^*))]^{t_i-1}\delta f(w_i)\right\}^{d_i}\left\{[1-\delta(1-F(w^*))]^{t_i}\right\}^{1-d_i}. \qquad (3.4)$$

Denoting $\pi(w^*) = 1 - F(w^*)$, the log likelihood function for the whole sample is given by,

$$\begin{aligned} l(\Theta, \mathbf{X}) &= \sum_{i=1}^{N}(1-s_i)\log\left\{1-\Phi\left[\frac{h(w_i^*)}{\sigma}\right]\right\} + \sum_{i=1}^{N} s_i \log\left\{\Phi\left[\frac{h(w_i^*)}{\sigma}\right]\right\} \\ &+ \sum_{i=1}^{N} s_i(t_i - d_i)\log(1-\delta\pi(w_i^*)) + \sum_{i=1}^{N} s_i d_i \log(\delta f(w_i)), \end{aligned} \qquad (3.5)$$

where $\Theta = (\sigma, \tau_1, \lambda, \delta, \Gamma_u, \rho)'$ is the vector of the structural parameters and $\mathbf{X}$ is the data matrix consists of observations on s, d, t, w, K, and b, as well as the estimated w^*.

It is well known that when the data employed are only duration and wage data, the likelihood function for a structural model is a monotonic function of w_i^*. This makes estimation irregular in the sense that the sample minimum of w_i would be the estimate for the reservation wage. The structural parameters that appear only in the reservation wage equation, such as the net search cost and the discount rate, cannot be obtained directly by the maximum-likelihood estimation. These can only be calculated after the estimation of the offer distribution and arrival rate parameters. However, by introducing the participation data in this study, the likelihood function is no longer monotonic in w^*. This can be seen clearly from (3.5). A clear advantage, then, of introducing participation data is that all the structural parameters in the model can be obtained by maximum likelihood estimation.

Another feature of the model is that it permits estimation of w^* for each job seeker in the sample, even in a representative agent model. This is contrary to the other structural models where the reservation wage is equal for all representative agents. Suppose the sample size is $N = N_1 + N_2$, where N_1 is the number of individuals who decide to search for new jobs, and N_2 the number of individuals who decide to withdraw. Suppose further that there are M structural parameters to be estimated in the model. If we treat each w_i^* as a parameter, then in total we have $N_1 + M$ parameters to be estimated. In principle, we should be able to identify all of them if $N_2 > M$. Of course, the number of parameters to be estimated will be extremely large if we estimate the reservation wages for each and every participant. We thus take advantage of the contraction mapping property related to the reservation wage equation. To see this in detail, we define a function $g(w^*)$ such that,

$$g(w^*) = w^* - b - \Gamma_u - \frac{\beta\theta}{1-\beta}\left(E[w|w \geq w^*] - w^*\right). \tag{3.6}$$

It then follows that,

$$\begin{aligned} g'(w^*) &= 1 + \frac{\delta\pi(w^*)}{\rho} > 0; \\ g''(w^*) &= -\frac{\delta}{\rho} f(w^*) < 0. \end{aligned}$$

Hence, the Newton–Rapshson procedure

$$w_{t+1}^* = w_t^* - \frac{g(w_t^*)}{g'(w_t^*)} \tag{3.7}$$

may be built into the iteration process for maximum-likelihood estimation and w^* may be updated at each step by the maximum-likelihood estimates of the structural parameters.

Many econometric packages provide canned procedure of maximum likelihood estimation, e.g. TSP, SHAZAM, LIMDEP. But the canned procedure cannot be applied here since w^* has to be updated in each step of parameter iteration. Special code for estimation has to be written.[3] On the other hand, the likelihood function (3.5) is highly non–linear, even without parameterization. In order to avoid taking

[3]The code for estimation is written in TSP, and through TSP, the code is linked to a number of Fortran procedures.

the second-order derivatives of the likelihood function with respect to the parameters, the BHHH algorithm is applied. Although this method is slow in iteration, the Hessian matrix equivalent in the iteration equation is always positive definite.

3.2 Estimation: A Representative Agent Model

This section, and the next, present some basic empirical results. The results under the specification given by equation (3.1) will first be presented. We then estimate the two-state representative agent model (where the search decision is ignored). Comparisons between the empirical results of the two- and three-state representative models are conducted in terms of their predictions and the effects of the structural parameters on the reservation wage (elasticities).

The introduction of the participation decision into the model makes it possible to directly estimate a number of structural parameters (such as discount rate or discount factor, employment and unemployment costs) through maximum-likelihood estimation. We estimate the models with data drawn from the 1986–1987 Canadian Labour Market Activity Survey (LMAS).[4] Briefly, the sample employed here consists of young men and women who have experienced a permanent job displacement during the year 1986. We have observations on their participation decision, unemployment benefits, duration of unemployment spells, accepted wages as well as the censoring indicator for the duration data.

Table 3.1 contains the estimates of the structural parameters for both male and female workers. All but the cost differential estimates are within expectations. The estimate of unemployment cost for male workers is \$0.2029 per hour and that for female workers is \$0.5694 per hour. It seems that the unemployment state for female workers is more costly than for male workers. However, neither of the two estimates is significantly different from 0 (their asymptotic t-ratios are 0.0593 and 0.3960, respectively). The estimate of unobserved heterogeneity in non-market time for male workers is higher than that for female workers (8.2361 vs. 3.4737), though the former has a t-value of 1.3773 only, while the later has a t-value of 2.6010. An

[4]Chapter 7 provides a detailed description on the sample employed.

interesting result is that male workers are more productive at home than for female workers (the estimated home productivity parameter τ_1 for male workers is 0.3161, while that for female workers is 0.3650. Again, the t-values for them are 1.0337 and 1.6326).

Table 3.1: Three-State Representative Agent Model Estimates

Group	Male		Female	
Parameter	Estimate	Asy. t-ratio	Estimate	Asy. t-ratio
Unobs. Heterogeneity (σ)	8.2361	1.3773	3.4737	2.6010
Home Productivity (τ_1)	0.3161	1.0337	0.3650	1.6326
Unemployed Costs (Γ_u)	0.2029	0.0593	0.5694	0.3960
Arrival Rate (δ)	0.1623	2.0869	0.0412	3.7584
Wage Offer (λ)	0.2911	7.4746	0.2918	8.0377
Discount Rate (ρ)	4.4579E-04	3.5694	4.6717E-03	2.2801
Log Likelihood	-454.839	–	-846.957	–
Sample Size	494	–	794	–

To make a comparison between male and female workers' home productivity, the following table calculates the monetary value (measured in $ per hour) of home productivity with respect to the number of children of the workers.

No. of Children	0	1	2	3
Male	3.1636	4.3397	5.9570	8.1661
Female	2.7897	3.9466	5.6852	8.1895

It seems that men value leisure more than women do. Without children, the value of a male's non-market time is $3.1636 per hour, higher than that of a woman, $2.7897 per hour. When children are present, the estimates show that the value of non-market time for women increases at a higher rate than for men. When the number of children reaches 3, the value of the non-market time for women is larger than that for men ($8.1885 per hour vs. $8.1661 per hour).

As expected, male displaced workers receive job offers more frequently than female displaced workers (0.1623 vs. 0.0412). The large gap between the estimated arrival rates for male and female displaced workers may reflect the fact that in our sample, 50.41% of the unemployed spells of male workers are completed, but only 33.25% of the unemployment spells of female workers are completed (see Tables 7.2 and 7.3). The wage distribution parameters estimated for men and women (0.2911 and 0.2918, respectively), imply that the mean wage offers for male and female workers are almost identical ($3.44 per hour). This may be because that observed heterogeneity is not taken into consideration in the representative agent model.

The estimated discount rates for male and female workers are, on a yearly basis, 23.14% and 24.18%, respectively. The almost identical discount rates for males and females are not surprising, given the fact that our sample consists of relatively young workers. The estimates are somewhat higher than one might expect, but since the individuals are displaced workers, unemployment status may have made them discount the future income at a higher rate. Compared to the empirical search work done previously, our estimate may be more reasonable. For example, with data on reservation wages of black young males, the estimated discount rate obtained by Holzer (1986) is between 19.6% and 53.3% for different sub-samples.

3.3 Comparison with the Two-State Model: Predictions

When the search decision is assumed to be exogenous, one obtains the two-state search model where fewer structural parameters can be identified, compared to the endogenous search model estimated in the previous section. In fact, only two structural parameters can be directly estimated in a two-state model, namely, λ and δ. Other structural parameters such as the cost differential, employment costs, unemployment costs and the discount rate that could be directly estimated in the three–state model now can only be calculated after the estimates on λ and δ are obtained. One also needs to fix w^* at a certain value.[5]

In order to make the results of the two- and three-state models comparable, and in order to take advantage of the contraction mapping property of the optimality condition, the study here assumes discount rates are equal to those estimated in the three-state model, and a zero unemployment cost is imposed for both male and female workers. The estimates for the structural parameters of the two-state structural model are summarized in the following table.

Still there is a large difference in offer arrival rates for male and female workers in the two–state model, though the mean wage offer difference is now larger than that implied by the three-state model estimated in the previous section. Assuming unemployment benefits are equal to \$2.5805 per hour (the average hourly UI benefit of

[5] Empirical works typically treat the discount rate as a known parameter. It can be estimated in the three–state model (see the previous section of this chapter), and also in the two-state model as done by Christensen and Kiefer (1994). However, in the two-state model, the estimation of the discount rate depends on one's estimate of the reservation wage. Since the likelihood function is increasing in reservation wage in the two-state model, the maximum likelihood estimate of the reservation wage is the sample minimum of the accepted wage data. For example, Christensen and Kiefer (1994) calculate the discount factor by solving their reservation wage equation as a function of the sample minimum of accepted wages, the estimates of offer probability and wage distribution parameters.

Table 3.2: Two-State Representative Agent Model Estimates

Group	Male		Female	
Parameter	Estimate	Asy. t-ratio	Estimate	Asy. t-ratio
Arrival Rate (δ)	0.1103	3.1801	0.0466	5.4270
Wage Offer (λ)	0.2460	8.2860	0.3086	10.8871
Log Likelihood	-720.684		-1061.83	
Sample Size	494		794	

the pooled male and female displaced workers), the effects of the structural parameter estimates on the reservation wage, the expected wage, acceptance probability and the escape rate of unemployment can be compared between the male and female groups, as well as over the two- and three-state representative models. The results are summarized in the following table.

Table 3.3: Prediction of the Representative Agent Models

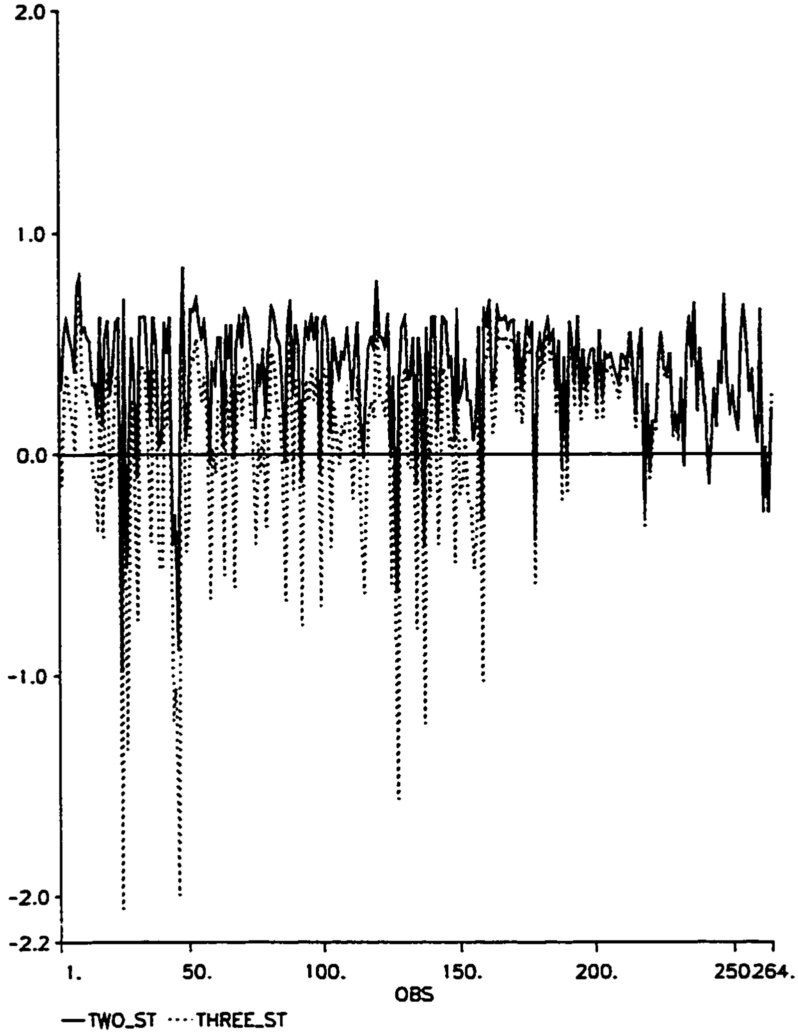
Group	Male		Female	
Variable	Two-state	Three-state	Two-state	Three-state
Reservation Wage	11.4478	8.7096	8.4037	6.2430
Expected Wage	15.5132	12.2457	11.6443	9.1534
Acceptance Prob.	0.0599	0.0852	0.0748	0.1171
Hazard Rate	0.0066	0.0124	0.0025	0.0059

Not all predictions of a structural model can be verified. For example, if an individual's reservation wage is not observable, then there is no straightfoward way to determine if the predicted reservation wage is accurate. But the predicted wage can be easily verified with the actual accepted wage for those who escaped the unemployment state. On the other hand, as might be expected, predictions based on the estimates of the representative agent models are typically not accurate, since observed heterogeneity is not taken into consideration. Nevertheless, we can still determine the accuracy of the predictions of the two- and three-state models. On average, the expected wages implied by both models, for both males and females, are higher than the actual accepted wages. However, the prediction errors of the three-state model are considerably lower than those of the two-state model. On an individual basis, the prediction gaps of the two models for male and female workers are presented in Figures 3.1 and 3.2. From the two sets of figures, it is easy to see that, for workers who receive higher wage compensation, the two models give almost identical predictions. For all other wage rates, the prediction gap implied by the three-state model is consistently lower than that for the two-state model. However, at the lower wage level, the prediction made by the two-state model is less volatile than that of the three-state model.

3.4 Comparison with the Two-State Model: Elasticities

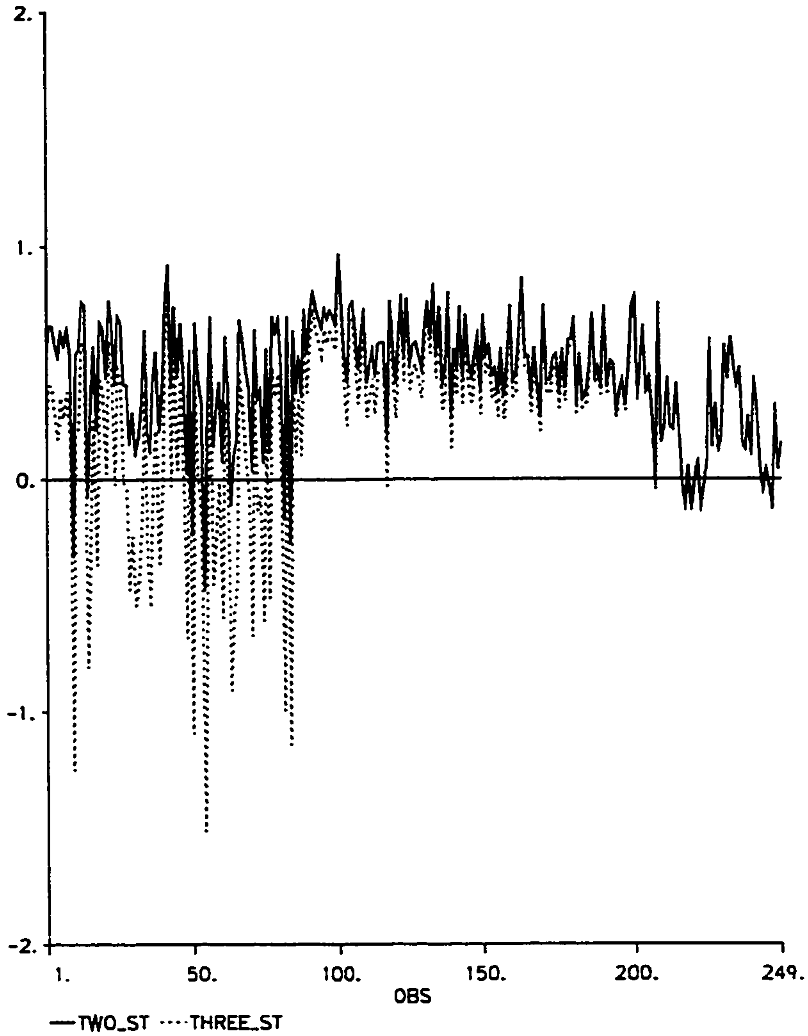
The elasticities of the reservation wage and the hazard rate with respect to the UI benefit have been extensively studied in empirical work. In general, the elasticities implied by reduced form studies are lower than those implied by regression studies, while the elasticities implied by structural studies are lower than those implied by the reduced form work. The calculation using the current estimates seems consistent with this tendency. The detail for the two- and three-state models are presented in Table 3.4.

Figure 3.1: Gap between Expected and Actual Accepted Wage: Female Group*



*. Solid curve stands for prediction error made by the 2-state model, dotted curve stands for the prediction error made by the 3-state model. The prediction error is calculated as a percentage difference between expected and accepted wages. The vertical axis represents the percentage error while the horizontal axis represents the individuals who accepted a new job.

Figure 3.2: Gap between Expected and Actual Accepted Wage: Male*



*. Solid curve stands for prediction error made by the 2-state model, dotted curve stands for the prediction error made by the 3-state model. The prediction error is calculated as a percentage difference between expected and accepted wages. The vertical axis represents the percentage error while the horizontal axis represents the individuals who accepted a new job.

Table 3.4: Elasticities of the Two- and Three-State Models*

Group		Male			Female		
Model	Variable	Resv. Wage	Hazard	Part. Pr.	Resv. Wage	Hazard	Part. Pr.
	b	0.1402	0.4412	—	0.1084	0.2533	—
Two-	ρ	0.1725	0.5426	—	0.2269	0.5301	—
State	δ	0.1725	0.4574	—	0.2269	0.4699	—
	$1/\lambda$	0.7151	3.2818	—	0.7570	2.5042	—
	b	0.1085	0.2661	0.0520	0.1095	0.2350	0.0574
	ρ	0.3086	0.7600	0.1484	0.2836	0.6084	0.1486
Three-	δ	0.3086	0.2400	0.1484	0.8326	0.3916	0.1486
State	$1/\lambda$	1.0686	2.6736	0.0411	0.8920	2.3710	0.0552
	τ_1	—	—	0.1814	—	—	0.2138
	K	—	—	0.0233	—	—	0.0318

*. All items are absolute values.

The three-state endogenous search model studied in this chapter implies that the elasticities of reservation wages with respect to UI benefits for male and female workers are 0.1085 and 0.1095 respectively. For males, the calculated elasticity is considerably lower than the figure implied by the two-state model (0.1085 vs. 0.1402), but the two models produce almost the same result for females. In terms of the elasticities of the hazard rate with respect to UI benefits, the two-state model produces higher results for both males and females. For male workers, the difference implied by the two models is more substantially (0.441 vs. 0.266 for male, compared to 0.253 vs. 0.235 for female).

In addition to the above elasticities, we have calculated the elasticities of the reservation wage and hazard rate with respect to the discount rate (ρ), the offer arrival rate (δ) and the offer distribution parameter ($1/\lambda$). The three-state model enables us to calculate the participation attitude with respect to the UI benefit, the discount rate, the offer arrival, the mean of the wage distribution, home productivity, and the number of children (at the average). The finding of this chapter suggests that for both male and female workers, the wage distribution parameter (human capital factor) is the most important factor, followed by the discount rate, in affecting the reservation wage and the the escape rate of unemployment. The elasticities of the reservation wage and the participation probability with respect to the arrival rate and the discount rate are equal to each other in absolute value. The elasticity of the reservation wage with respect to these two factors suggested by the three-state model is higher than that generated by the two-state model. It also can be seen that the hazard elasticity with respect to the escape rate in the three-state model is much higher than that in the two-state model, although we are unable to tell which model is more accurate. Compared to all these variables, our study shows that the UI benefit plays a less important role in affecting the reservation wage, the escape rate, and the participation decision. The results also suggest that the participation decision is most responsive to home productivity for both male and female (.18 vs. .21) displaced workers. This is followed by the arrival rate and the discount rate. The participation decision is less responsive to human capital and the child status for both male and female workers, although females' decisions are more responsive to human capital and child status, compared to their male counterparts.

3.5 Concluding Remarks

This chapter discusses the econometric model and the estimation strategy for the three-state search model.

Two representative agent models are estimated. The results are consistent with most findings in the empirical search literature, but a comparison between the estimates of two- and three-state representative models reveals that the two-state model may have overestimated the effects of the unemployment insurance benefit provisions. Moreover, we found that the cost differentials between the employment and unemployment states for both males and females are very close to 0, and not significant. Based on this finding, we also estimate a restricted version of the model, from which one can see that discount rate estimates for both genders are almost identical. Given that our sample consists of relatively young workers, this is not surprising.

Given that observed heterogeneity is not taken into consideration, the predictions on the expected wages made by both the two- and the three-state models are not very accurate, but the prediction errors made by the three-state model are lower than those made by the two-state model for most individuals. For only a small number of individuals whose accepted wages are at the higher end of the range, the two models produce identical prediction errors.

Chapter 4

Application: The Effects of Child Care Costs

This chapter will apply the three-state search model to investigate the effects of young children on the decision to search, offer arrival probability, the reservation wage, and the duration of unemployment of the displaced female workers. The behavioral difference of married and lone women is also studied.

4.1 Introduction

The effect of young children on the labor market behavior of households, particularly on female workers, has been widely studied in recent years. Indeed, upon having children, a household needs to allocate a significant amount of resources to child care activities. The time needed for child care activities will directly reduce the time allocated for the market and/or the time allocated for leisure, and, as suggested in Chapter 2, the monetary costs of child rearing, e.g. day care costs, may be viewed as the costs of working for the employed workers. As such, a number of aspects of the labor market behavior of female workers will be affected by the presence of young children.

Among the aspects studied are the effect of young children on the labor force participation, the effect on hours of work, and the effect on the wage rate (or earnings) of female workers. Studies on the effect of young children on household labor supply[1] found that the presence of young children reduces both the likelihood of labor force participation and the hours of work (if they decided to work). Studies on female earnings, dating back to Mincer and Polachek (1974), found the relationship between female wages and fertility to be negative.

These studies have attracted a number of criticisms in terms of their econometric modelling. Notably, the potential endogeneity of family size, the misspecification of the earning functions, the robustness of the estimates and the selectivity bias. However, a more significant problem of the studies is that the dynamics of the labor market behavior of female workers has been literally ignored. It is easy to see that the resource allocation of a household on child care activities is quite different from the resource allocation on most other goods and services, in that that the household has to continually allocate its resources on the same item–child care–over a long period of time. However, due to the dynamic nature of the labor market, the labor market status of a worker may experience a number of transitions over this time period. A change in the labor market status may cause the worker in question to re-assess the optimality of his/her labor market activities for the next period. Hence, we believe that it will be more interesting to model the effects of child care activities within the job search framework.

The job search theory has been applied to the labor market behavior of unemployed male workers by a large number of authors. Typically, the exogenously displaced male workers are assumed to start searching for a new job immediately after being laid off. This may not be the case for female displaced workers, particularly for the younger females who have given births. Clearly, women who have given births prior to the displacement will now face some new costs related to child rearing activities. Hence, they have to re-assess the costs and benefits arising from the new situation. The decision to search (or drop out of the labor force), the reemployment reservation wage, the arrival rate of job offers, and the duration of unemployment are all likely to be affected by the presence of young children (because child care is also time consuming and may reduce their time available for job search).

[1] See Browning, 1992, for a survey.

This chapter is concerned with the econometric modelling of the search behavior of young female displaced workers with young children. In the next section, we adapt the theoretical model to incorporate the child status for the displaced female workers and specify the econometric model. Section 3 gives the details of the empirical results. In Section 4, the estimation will be done for married and single women separately. The simulation results are presented in Section 5, and Section 6 contains the conclusion.

4.2 The Model and the Econometric Specification

The search model applied to the female displaced workers is the one developed in Chapter 2. All the assumptions discussed there are maintained except that here we explicitly take child care costs as the only cost for all workers. Hence,

$$\begin{aligned} \Gamma_e &= \Gamma_e(K) = \gamma_{e0} I(K) + \gamma_{e1} K \\ \Gamma_u &= \Gamma_u(K) = \gamma_{u0} I(K) + \gamma_{u1} K \end{aligned}$$

where K is the number of children and $I(K)$ is the indicator of child status with $I(K = 0) = 0$ and $I(K > 0) = 1$. For those women who have no children, $\Gamma_u(0) = \Gamma_e(0) = 0$, i.e. work and search are costless for women who have no children. The child care costs for the nonparticipants are assumed to be 0, that is, child care activities are conducted privately for those who decide to withdraw. The above specification assumes child care costs to be state dependent. We believe state dependence of child care costs is an important issue. It allows us to take into account the fact that search activities typically consume less time than a full-time job, and hence a portion of child care costs may be avoided while unemployed. Of course, this asymmetry in the effects of the presence of young children on the net values of employment and unemployment might also be attributed to the government subsidy and tax deduction of child care costs for those who are working or looking for jobs.

Given the assumptions, it is straightforward to derive the optimality condition for the displaced female workers.

$$w^* = b + \Gamma(K) + \frac{\delta}{\rho\lambda}\exp(-\lambda w^*) \tag{4.1}$$

where $\Gamma(K) = \Gamma_e(K) - \Gamma_u(K)$, represents the difference in child care costs between the reemployed and the unemployed, searching workers. Clearly, the escape rate of unemployment will be affected by child status and child care cost differentials between the employment and the unemployment states. The necessary and sufficient condition for a displaced worker to remain in the labor force is given by,

$$\frac{1}{1-\beta}\left(\frac{1}{\tau_1}\exp(\tau_1 K)\right) \leq b - \Gamma_u(K) + \beta E[V] = \frac{1}{1-\beta}[w^* - \Gamma_e(K)] \tag{4.2}$$

where w^* is given by equation 4.1.

The model is informative and flexible. It predicts that the participation decision is negatively related to child status. For those who decide to search for new jobs, if the offer arrival rate (δ) is independent of the presence of children, reservation wages and the unemployment spell lengths can be raised by the presence of young children if child care costs in the employment state exceed that in the unemployment state ($\Gamma_e(K) > \Gamma_u(K)$). While if $\Gamma_e(K) < \Gamma_u(K)$, reservation wages and the search spell lengths will be lowered. As a result, the model admits both negative and positive correlation between re-employment wages and fertility for female displaced workers. On the other hand, if δ depends on K, the effect of child status on reservation wages and unemployment duration will depend on the value of the relevant structural parameters. In the case where child care costs are symmetric between the employment and unemployment states and δ is independent of K, then the presence of children has no effect on reservation wages and the hazard rates of the unemployed workers.

The functional form of the log likelihood for the estimation is essentially the same here as in Chapter 3, except that the fixed as well as the variable child care cost parameters now enter into the estimation procedure. The estimation strategy we shall implement is also that of Chapter 3. However, by implicitly assuming child care costs as the only costs of employment and unemployment, the effect of child status can be investigated. To restrict the number of parameters to be estimated, the annual discount rate is assumed to be equal to 20% (which is essentially the same as the estimated annual discount rate for female workers in Chapter 3). With the introduction of the participation data, all the structural parameters of the search model, including the differential in child care costs between the employed and the unemployed states, the fixed and variable child care costs associated with the employed state and the unemployed state can be identified.[2]

4.3 Empirical Results: Full Sample

In this section, we present and interpret the main results obtained by implementing the model described in the previous section. As a first step, we implement the model using the entire sample of women. We then estimate a model where heterogeneity is captured by individual variations in UI benefit and child status. The parameters are therefore common to all women. We refer to this model as a representative agent model. With this model specification, particular attention is paid to whether child care costs are better described by fixed or variable costs. Subsequently, we consider model specifications where offer probabilities are affected by child status in order to capture the potential restrictions on search intensity for women who have young children, and where both the mean wage offer (λ) and the productivity parameter at home (τ_1) are allowed to differ according to the education classes.

4.3.1 The Representative Agent Model

By estimating the model with the entire sample, it is implicitly assumed that the dynamic optimization behavior of single and married (or cohabiting) women can be described by a representative agent model. The original sample (see Chapter 7) contains 980 women who have experienced a permanent job displacement. Out of these 980 women, around 7% have actually dropped out upon displacement, or decided not to search. The remaining women reported searching for a new job. They are divided into two groups: those who have actually accepted a new job and those who were still looking for work by the end of the survey period.

[2]Since $\Gamma(K) = \Gamma_e(K) - \Gamma_u(K)$, identification of the fixed and variable cost differentials and the fixed and variable cost parameters related to one labor market state enables us to derive the fixed and variable cost parameters associated with the other state.

Table 4.1 summarizes the estimation results. Column 1 of the estimates contains the result for the case where women are assumed to face only variable child care costs. The point estimate for home productivity (τ_1) is 0.623 with an asymptotic t-ratio of 3.11, indicating that the presence of young children raises productivity at home significantly. The values of home productivity are 1.61, 2.99, 5.58, and 10.40 for 0, 1, 2, and 3 children respectively. These values show that home productivity of a female worker rises with respect to the number of children at an increasing rate. However, the estimate for σ (3.6) with a t-ratio of 10.4, implies that there is a significant variation among them. The estimate for the offer arrival rate (δ) indicates that unemployed females have a 6% probability of receiving an offer each week, while the estimate for λ (0.359) implies that the mean of the wage distribution is \$2.79 per hour.

Table 4.1: Representative Agent Model (N=980)

	Variable Cost		Variable and Fixed Cost		Fixed Cost	
Parameter	Coefficient	Asy. t-ratio	Coefficient	Asy. t-ratio	Coefficient	Asy. t-ratio
Unobs. heterogeneity (σ)	3.6024	10.4238	3.9656	5.9737	3.4758	2.5963
Home Productivity (τ_1)	0.6231	3.1095	0.5581	1.7823	0.3526	1.3802
Cost Diff.: Fixed (γ_0)			0.2841	0.1810	-0.4380	-0.8763
Cost Diff.: Variable (γ_1)	-1.2259	-3.1552	-0.9224	-0.7785		
Fixed Cost: Unemployed (γ_{u0})			0.5822	0.1253	-0.1907	-0.1423
Variable Cost: Unemployed (γ_{u1})	1.2634	1.1631	-0.0714	-0.0193		
Offer Arrival Rate (δ)	0.0573	6.2633	0.0578	5.7399	0.0638	5.7051
Wage Dist. Parameter (λ)	0.3593	19.7250	0.3418	18.7059	0.3560	19.8720
Log Likelihood	-1377.22		-1231.7		-1233.60	

The estimated child care cost differential is \$-1.23, implying that unemployed search costs exceed child care costs associated with the employed state. Given the estimate of the variable child care costs while unemployed (\$1.26), we see that child care costs while employed are only about a few cents (This is, of course, the net costs). The negative cost differential suggests that female workers with young children tend to accept lower paying offers than those who do not have children.[3]

The specification just presented relies solely on the variable child care costs. This might be questioned by those who would support the hypothesis that child care arrangements might be similar for those women who have more than one young children. The second column of the estimates in Table 4.1 contains our estimates of the representative agent model with a cost structure that allows both the fixed and the variable child care costs to enter the model with $\gamma_0 = \gamma_{e0} - \gamma_{u0}$ representing the fixed child care costs differential, and $\gamma_1 = \gamma_{e1} - \gamma u1$ representing the variable child care costs differential. However, the result indicates that the data cannot distinguish between fixed and variable costs. This might be explained by the fact that, in our sample, very few women have more than one child. It is worthwhile to point out that other estimated structural parameters, such as home productivity, offer arrival rate, and the wage distribution, appear invariant to the inclusion of fixed child care costs.

We also estimate a specification where women are assumed to face only fixed child care costs. The result is contained in the last column of Table (4.1). With regard to the various costs parameters, this specification produces similar estimates to the model with both fixed and variable child care costs. The only notable change is the estimated home productivity parameter (0.3526, compared to 0.6231 and 0.5581 for the other two specifications) which is lowered substantially, but it has an asymptotic t-ratio of 1.38, indicating a lack of significance at any conventional level.

In summary, our estimation of the representative agent model seems to suggest

[3]The exact magnitude of this effect depends on the predicted reservation wages. As we shall see in section 5 of this chapter where various simulations are conducted, the representative agent model (with variable child care costs) predicates the reservation wages range from \$1.86 to \$7.37, with an average of \$6.27 for the sample. Hence the effect ranges approximately from -15% to -61% with an average of -49% of the total cost differential.

that the model with variable child care costs is more appealing compared to the other two specifications. We can easily see from the model with variable child care costs that child status does raise the propensity to withdraw from the labor force, and reduce the reservation wage by raising the unemployment costs. In addition, the lowered reservation wage implies that the escape rate out of unemployment will be higher for the unemployed women with young children.

4.3.2 Models with Parameterizations

We now consider generalizations of the representative agent model (with only the variable child cost) by incorporating the parametrizations of the offer arrival rate δ, home productivity τ_1, and the mean wage offer λ with child status and the education class variables.

First, we allow the offer arrival rate to depend on child status. This might be highly relevant if, for instance, women with young children searching for a new job are less flexible or have less time to devote to search activities compared to those who have no children. To take this into account, we specify the offer probability as

$$\delta = \exp(\delta_0 + \delta_1 K)$$

where K represents the number of young children. δ_1 is expected to be negative. But this specification may be criticized for ignoring the fact that females with different levels of education (human capital) do not search from the same wage distribution. For this reason, we shall also consider the following parametrization for the mean wage offer,

$$\lambda = \exp(\lambda_0 + \lambda_1 \; Primary + \lambda_3 \; University)$$

where Primary and University are dummy variables indicating the highest education level attained by a woman. Notice that those with high school education are classified as the reference group. Finally, we will allow the productivity at home (τ_1) to be a function of education in order to see whether a woman with a higher level of human capital would also be more productive at home. We specify τ_1 as

$$\tau_1 = \exp(\tau_{10} + \tau_{11}\ Primary + \tau_{13}\ University).$$

Table 4.2 contains our estimation results.

Table 4.2: Parameterized Models (N=980)

Model	Model I		Model II		Model III	
Parameter	Coefficient	Asy. t-ratio	Coefficient	Asy. t-ratio	Coefficient	Asy. t-ratio
σ	3.6181	4.4709	3.9169	5.8313	4.1707	3.1093
τ_1	0.4383	1.8955	0.4721	2.8311	–	–
τ_{10}	–	–	–	–	-1.3626	-3.0956
τ_{11}	–	–	–	–	0.8701	1.5664
τ_{13}	–	–	–	–	-0.5893	-2.5259
γ	-0.9614	-1.8152	-0.4435	-0.9902	-0.0559	-0.1078
γ_u	-0.6105	-0.5375	-1.2052	-0.9773	-2.4608	-2.3236
δ_0	-2.6296	-15.5163	-2.4267	-13.40007	-2.7056	-11.5011
δ_1	-0.3956	-2.7354	-0.3487	-2.4448	-0.4455	-2.4587
λ	0.3667	20.2508	–	–	–	–
λ_0	–	–	-0.8693	-17.0328	-1.0452	-15.6595
λ_1	–	–	0.2373	5.3880	0.2999	3.6504
λ_3	–	–	-0.1724	-5.9508	-0.4454	-10.9756
Log L.	-1336.42	–	-1323.04	–	-850.901	–

The first case (Model I in Table 4.2) we estimate is the one where only the offer arrival rate δ is parameterized as a function of child status. As can be seen upon looking at the estimates, the unobserved heterogeneity σ and wage distribution λ parameters are very robust compared to the estimates in the representative agent model (the model with variable child care cost, see Table 4.1). While home productivity now seems to be higher than that suggested by the representative agent model, it only has an asymptotic t-value of 1.896.[4] The important finding of this model is that child status does affect the offer arrival rate by a significant magnitude. The point estimates for δ_0 and δ_1 are -2.6296 (with a t-value of -15.5163) and -0.3956 (with t-value of -2.7354), respectively. The estimates suggest that the offer arrival rate would be 0.049 per week for a women with a child, while a woman who has no children would receive job offers at a rate of 0.072 per week.[5] It is interesting to note that the estimated cost differential between employment and unemployment becomes narrower compared to the estimate in Table 4.1. It also has a lower (absolute) t-value now (1.81 vs. 3.16).

The second parameterization (Model II in Table 4.2) allows job arrival rate as a function of child status and the mean wage offer as a function of education. Clearly, the estimates on unobserved heterogeneity, home productivity, and even the effect of child status on job arrivals are similar to those obtained under Model I. The effect of education on the wage distribution parameter is just as one might easily expect, human capital does affect the mean wage offer in a significant way. For a woman with only primary education, the mean of the wage offer distribution estimated would be \$1.89 per hour, while women with a university degree are expected to draw job offers from a wage distribution with mean of \$2.86 (for a woman in the reference education class, this is \$2.31). Perhaps the most interesting finding in this model is the employment and unemployment cost differential. It is now estimated

[4]It shall be noticed that when τ_1 is below 1, home productivity changes in the opposite direction to the value of τ_1.

[5]The case where education variables together with child status enter the offer arrival rate function has also been estimated. The result shows that when the wage distribution parameter λ is parameterized as a function of education, the offer arrival rate does not seem to be affected by education at any level of significance.

to be -\$0.4435 with a t-value of -0.9902. This compares to -\$1.226 (t=-3.16) of the representative agent model and -\$0.9614 (t=-1.82) of Model I.

The last column of Table 4.2 contains our preferred and the most general model specification, where home productivity and mean wage offer are parameterized as a function of education, and the offer arrival rate as a function of child status. The likelihood ratio tests clearly favor this model. The results are quite striking. We find that child status reduces the offer arrival rate more heavily than that implied by Models I and II. While in those two models, the presence of one child reduces the offer arrival rate by about 30%, this becomes 36% in Model III. The effect of education on the mean wage offer is more evident in Model III than in Model II. Model III implies that the mean wage offer for the three education classes are \$2.11, \$2.84 and \$4.44 respectively. The difference between the mean wage offers received by women with university degrees and women with only primary education is \$2.33, compared to that of \$0.97 (\$2.86 - \$1.89) in Model II. More importantly, with the introduction of education into the home productivity parameter, we find that, with or without children, women who received university training are substantially more productive at home than women who belong to the lower education classes, as can be seen from the following table, where home productivity (in \$ terms) is calculated with respect to the number of children, based on the estimated values of τ_1.

	Primary	Secondary	University
τ_1	0.61	0.26	0.14
K=0	1.64	3.85	7.04
K=1	3.02	4.99	8.22
K=2	5.55	6.47	9.45

The difference in home productivity between a university educated woman and a woman who only completed primary education can be as large as \$5.40 per hour when there are no children present. The gap shrinks to \$3.90 as the number of children increases from 0 to 2. It is interesting to observe that for a woman who belongs to the primary group, when the number of children increases from 1 to 2, her home productivity will increase by as much as \$2.53, but for a woman with a university degree, the same change in the number of children only results in an increase in her home productivity of $1.23. This may lead us to the observation that the growth of home productivity of an under-educated woman is mainly due to the increase in her number of children, while for a woman with university degree, the higher home productivity is basically contributed by her education (intrinsic human capital). Given this and the significant effect of education on the mean wage offer, we see that women with higher education are more productive both at home and in the labor market.

Yet more interestingly, we find that the unemployment search costs and employment child care costs are essentially equal to each other under the more general specification. As can be seen from Table 4.2, the cost differential is now -$0.0559 with a t–value of -0.1078. Hence the difference is totally insignificant. This result leads us to believe that the lower reservation wages of women with young children is due to the lower offer arrival rate which in turn is caused by the presence of young children.

Finally, we also obtain the estimates for the employment and unemployment costs. The latter ($-2.46 with t-value=-2.3236) is directly estimated in the model; it implies that the employed child care costs are equal to $-2.52 with a t-value of -2.34. However,without additional data, one would not be able to find the sources contributing to these negative cost estimates. The possible sources are government subsidies for women with children who are working or actively looking for jobs, or financial support from a spouse, or income from investments. One variable available in the LMAS data is the marital status which shall be explored in the next section.

4.4 Married and Lone Women

This section is devoted to the separate analysis of women who are married (including those who are cohabiting) and women who are single. The distinction is likely to be important as those women who are married (or are cohabiting) might have access to financial support (not reported in the LMAS) other than only Unemployment Benefit. As a consequence, we have implemented the representative agent model of Table 4.1 on a sub-sample of 574 married (or cohabiting) women and a sub-sample of 406 single women.

Table 4.3: Married and Single Women

Group	Married Women		Single Women	
Parameter	Coefficient	Asy. t-ratio	Coefficient	Asy. t-ratio
Unobs. heterogeneity (σ)	3.3716	10.9125	3.1511	9.0858
Home Productivity (τ_1)	0.7020	3.1753	1.2495	1.5823
Cost Diff.: Variable (γ_1)	-1.6563	-3.6404	-1.7244	-0.7658
Variable Cost: Unemployed (γ_{u1})	2.0180	1.8526	0.4896	0.0555
Offer Arrival Rate (δ)	0.0473	5.4144	0.04768	2.2223
Wage Dist. Parameter (λ)	0.3214	15.1669	0.4092	11.8055
Log Likelihood	-812.854		-758.901	
Sample Size	574		406	

Overall, the results for married women are quite similar to those obtained for the full sample. We do, however, note two important distinctions. In particular, the estimate for τ_1 (0.702) implies that the value of the non-market time of married women is (on average) \$1.42 per hour with no children, \$2.88 in the presence of one child and \$5.80 with two children. The estimated τ_1 (1.25) for single women suggests that they are less productive in the absence of children (\$.80 per hour) and almost equally productive with one child (\$2.80 per hour) but are substantially more productive at home with two children (\$9.75). It is worth to notice that the equality of unemployment search costs and employment child care costs is failed to be rejected for single women (unlike the case for married women). This might be explained by the fact that single women are more likely to have access to subsidized child care services, and/or are often more heavily subsidized when employed than married women. Indeed, the estimates on the unemployment search costs for married women (2.0180) and single women (0.4896) imply that the employment child care costs for married women and single women are 0.3617 and -1.2348, respectively. That is, married women incur a positive child care cost when employed, while single women receive a subsidy (negative cost) when employed (though the latter has only a small t-value).

In Table 4.4, we implement our most general model specification (the same as the last column of Table 4.2) to both married and single women. Again, in both cases, we do not reject the null hypothesis that child care costs in the employment and unemployment states are equal, although the point estimate for the difference in child care costs of single mothers, -\$0.85 per hour, is more important than the one obtained for married mothers (-\$0.3119 per hour). The alternative costs estimates for married and single women in this more general model all become insignificant. This is consistent with our findings about the cost measurements in the representative agent model: the search costs and the employment costs are practically equal for all women and are not basic factors in affecting a woman's reservation wage.

The estimated coefficients on K in the parameterization of δ are -0.4395 (with a t-value of 2.9673) and -0.1096 (with a t-value of 0.2669) indicating that the search behavior of married women is affected by the number of children, while the search behavior of single women is less affected by the number of children. However, for lone mothers (unlike married mothers), the null hypothesis that offers are received independently from child status fails to be rejected.

The overall results also indicate that lone mothers are more productive at home than married mothers in the lowest education class (estimated τ_1 are 0.7239 for married women, and 0.2377 for single women). For the other two education classes, married women are more productive at home than single women. Within the highest education class, married women are substantially more productive at home than single women (estimated τ_1 for married women is 0.1716, compared to 0.7813 for single women).

4.5 Some Simulations

Having obtained the maximum likelihood point estimates for the structural parameters with various model specifications, we can now numerically analyze the effects of child status on a woman's reservation wage (and therefore mean accepted wages), re-employment hazard (and hence the duration of unemployment), the acceptance probability and on the probability of specializing in household (child care) activities. Without loss of generality, we evaluate these economic variables at the mean level of UI benefit in the sample. As some specifications have introduced education as a key variable (using standard human capital arguments), we shall also analyze the effect of child status together with the various education levels.

Table 4.5 contains the simulation results for the representative agent models with various cost structures. Our preferred model, Model I, where only the variable costs are involved, very clearly indicates the impact of child status. When the number of children increases from 0 to 2, the reservation wage can drop from \$6.22 to \$3.77 per hour. Consequently, the escape rate out of unemployment rises from 0.006 (when K=0) to 0.015 (for K=2), while the acceptance probability goes from 0.11 to 0.26. As expected, the participation probability drops sharply when K increases from 0 to 2. Similar patterns appear in the simulations of the other two models.

Table 4.4: A General Model for Married and Single Women

Group	Married Women		Single Women	
Parameter	Coefficient	Asy. t-ratio	Coefficient	Asy. t-ratio
σ	2.4932	2.5328	3.8216	1.6626
τ_{10}	-1.3793	-3.0787	-0.4767	-0.2024
τ_{11}	1.0562	1.2149	-0.9900	-0.5317
τ_{13}	-0.3833	-1.8963	0.2001	0.1486
γ_1	-0.3119	-0.6528	-0.8465	-0.2378
γ_{u1}	-1.0762	-1.1119	0.6483	0.0598
δ_0	-2.1821	-8.4794	-2.8081	-9.1598
δ_1	-0.4395	-2.9673	-0.1096	-0.2669
λ_0	-0.8217	-11.2108	-1.0007	-9.3519
λ_1	0.2719	4.4082	0.3268	1.2968
λ_3	-0.2412	-6.2438	-0.1532	-1.9773
Log Likelihood	-772.679		-573.30	
Sample Size	574		406	

Table 4.5: Simulations for the Representative Agent Models*

Models	Model I			Model II			Model III	
Child Status	K=0	K=1	K=2	K=0	K=1	K=2	K=0	$K \neq 0$
Reser. Wage	6.2185	4.9926	3.7767	6.4410	5.8027	4.8803	6.3177	5.8797
Acpt. Wage	9.0017	7.7758	6.5499	9.3666	8.7283	7.8060	9.1267	8.6887
Acpt. Prob.	0.1071	0.1663	0.2584	0.1106	0.1326	0.1886	0.1055	0.1233
Hazard Rate	0.0061	0.0095	0.0148	0.0060	0.0080	0.0109	0.0067	0.0079
Drop Prob.	0.1001	0.2929	0.7000	0.1200	0.2401	0.4468	0.1582	0.2384

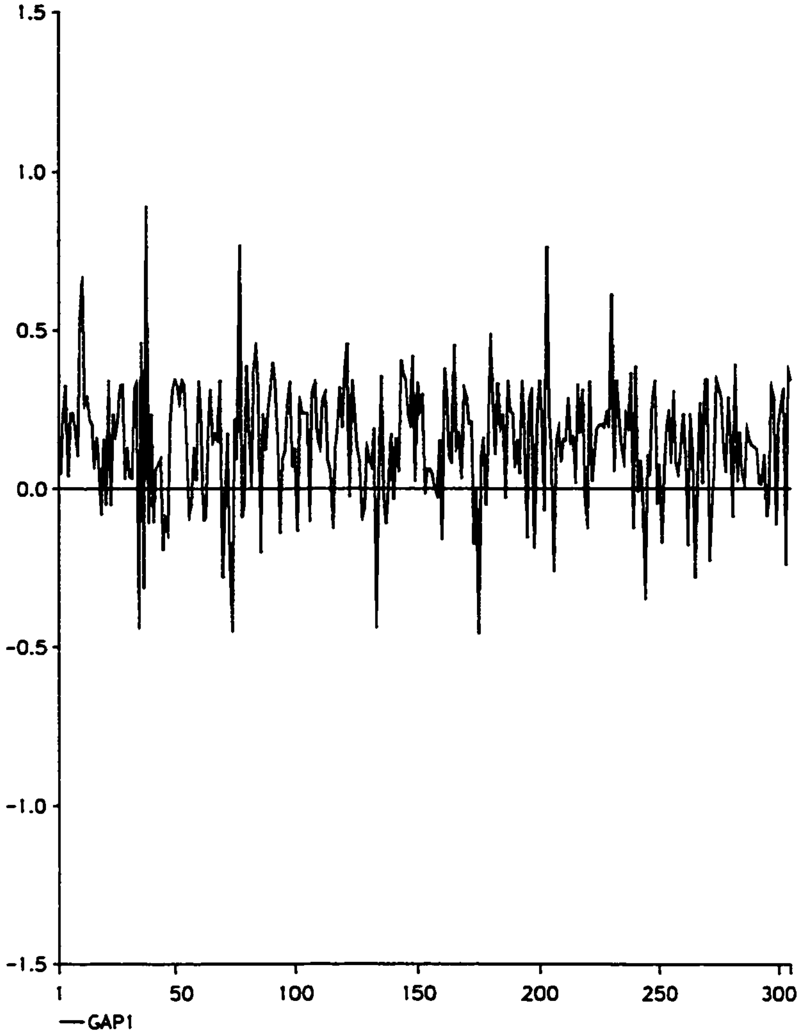
*. The calculations are based on average hourly UI benefits of $1.8491.

The expected wages are also calculated for each individual in the sample. A comparison can be made between the actual accepted wages of those who accepted offers and the wages predicted by the model. This is illustrated by Figures 4.1–4.3. Evidently, the specification with variable cost only, predicts the accepted wages more accurately than the other two specifications.

The simulations for the parameterized models are presented in Table 4.6. The results under Model I, where δ is parameterized by child status, is similar to those of the representative agent models, particularly the variable cost specification, except the effect of child status on the reservation wage is sharper in the parameterized model since this model allows child status to affect the reservation wage not only through the cost differential but also the offer arrival rate. Model II isolates the effect of human capital from the effect of child status. One still can see clearly the effects of child status on reservation wage and drop out probabilities. Among the three education levels, the effects of child status on reservation wages are almost the same: reservation wages are halved when the number of children increases from 0 to 2. With δ, λ, and τ_1 all parameterized, Model III gives us a fuller picture of the effects of child status and the human capital endowment. The results show that, while child status is still an important factor, the effect of education is stronger in affecting female workers' reservation wages and participation decisions. This is consistent with predictions of the standard human capital theory. As far as the effect of child status is concerned, it seems that for different education groups, it affects reservation wage and drop out probability through different channels. One may notice that, among the university educated group, the effects of child status are very strong. For example, when the number of children increases from 0 to 2, the reservation wage decreases from \$16.14 to \$7.60, while drop out probability increases from 1.5% to 21.6%. The effect of child status for the lower education group is less obvious, but not very hard to identify. Among the two lower education groups, while acceptance probabilities increase as the number of children increases, the hazard rates are quite stable regardless of the number of children. This indicates that the effect of child status on reservation wages is primarily channeled through the offer arrival rate for these two groups.

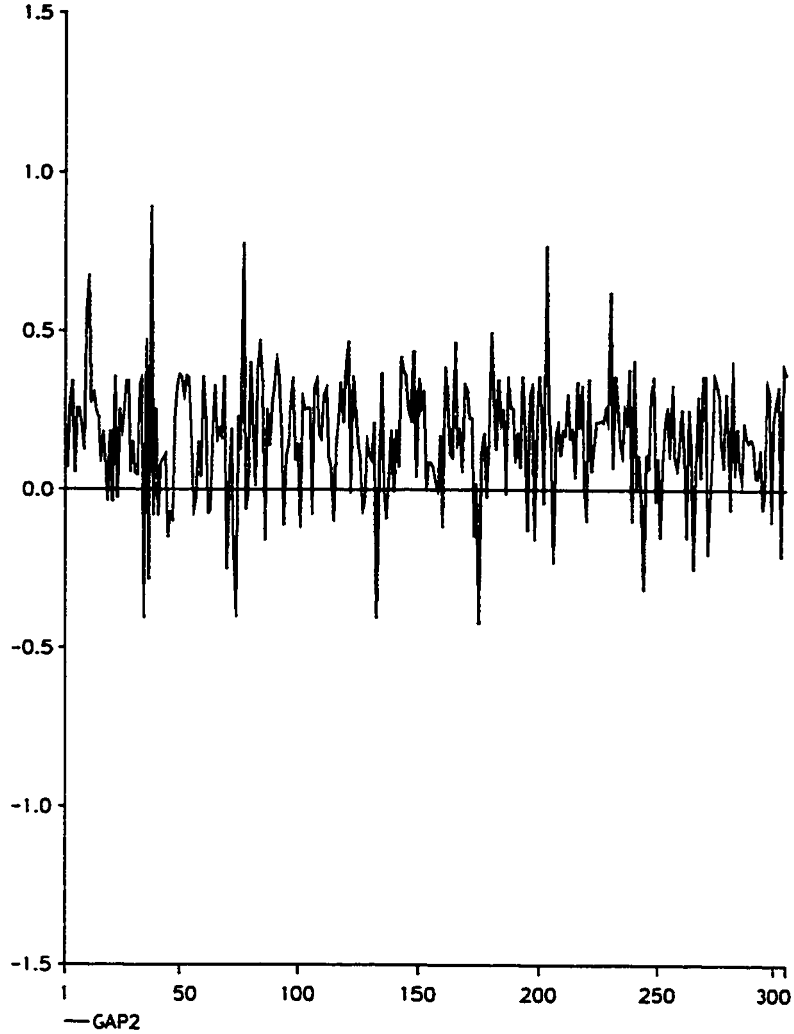
The prediction gaps between expected and accepted wages for these models are illustrated in Figures 4.4 – 4.6. As expected, the prediction gap of the fully parameterized model (Model III) is the smallest among the 3 parameterized models.

Figure 4.1: Gap between Predicted and Actual Wages: Representative Agent Model with Variable Cost



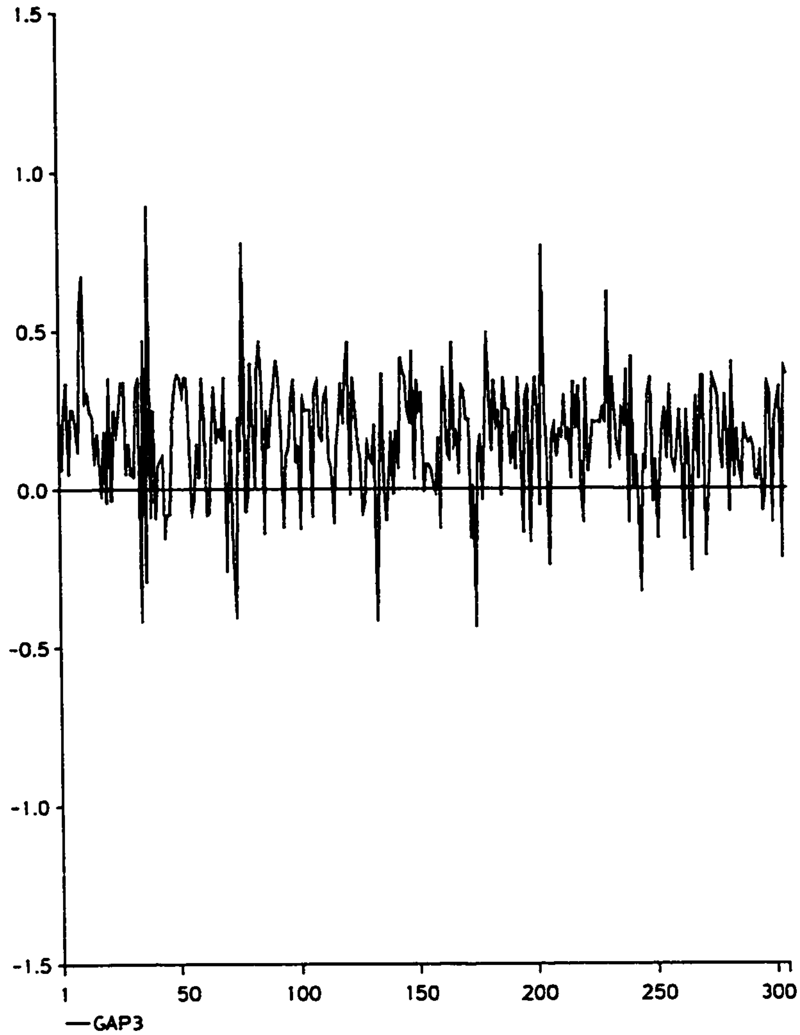
*. The prediction error is calculated as a percentage difference between expected and accepted wages. The vertical axis represents the percentage error while the horizontal axis represents the individuals who accepted a new job.

Figure 4.2: Gap between Predicted and Actual Wages: Rep. Model with both Costs



*. The prediction error is calculated as a percentage difference between expected and accepted wages. The vertical axis represents the percentage error while the horizontal axis represents the individuals who accepted a new job.

Figure 4.3: Gap between Predicted and Actual Wages: Rep. Model with Fixed Cost



*. The prediction error is calculated as a percentage difference between expected and accepted wages. The vertical axis represents the percentage error while the horizontal axis represents the individuals who accepted a new job.

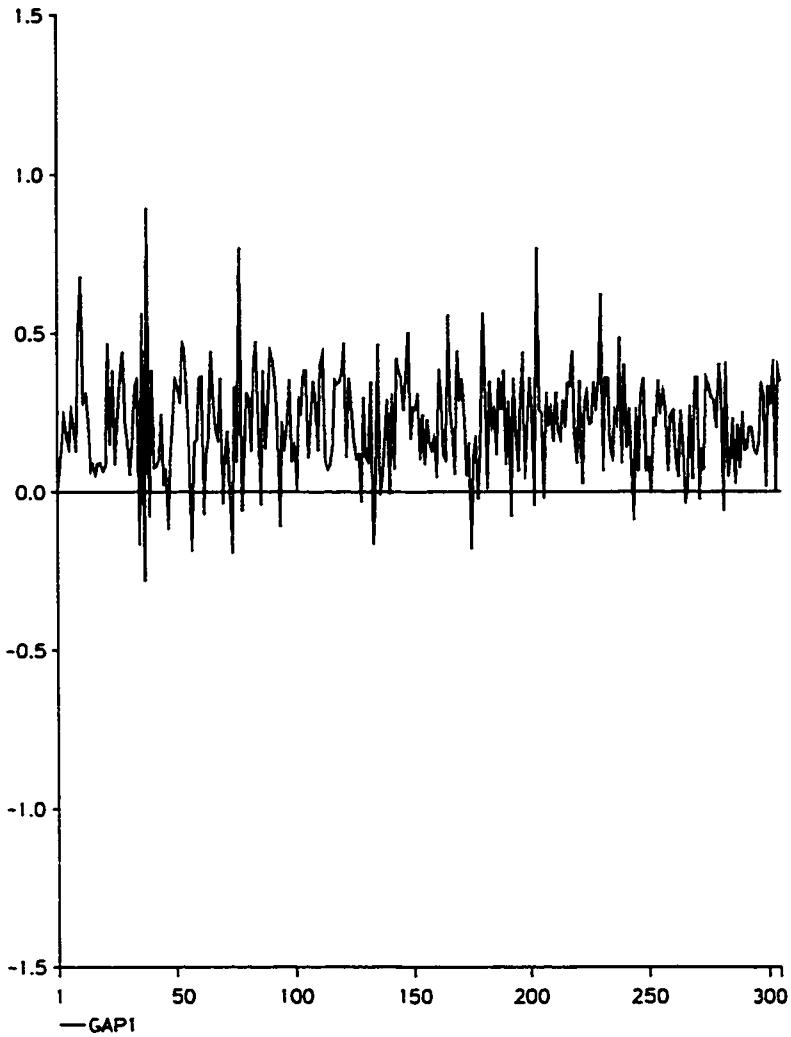
Table 4.6: Simulations for Parameterized Models

Models		Model I*			Model II			Model III		
Education	Child Status	K=0	K=1	K=2	K=0	K=1	K=2	K=0	K =1	K=2
Primary	Reser. Wage	6.7925	4.2172	2.1672	3.4301	2.5212	1.7493	2.9494	2.4980	2.1887
	Acpt. Wage	9.5195	6.9430	4.8942	5.3115	4.4026	3.6307	5.0563	4.6048	4.2956
	Acpt. Prob.	0.0828	0.2131	0.4517	0.1615	0.2618	0.3946	0.2466	0.3056	0.3538
	Hazard Rate	0.0060	0.0103	0.0148	0.0143	0.0163	0.0174	0.0165	0.0131	0.0097
	Drop Prob.	0.1062	0.2669	0.5188	0.3688	0.4217	0.5405	0.3765	0.3158	0.3447
Secondary	Reser. Wage				5.8440	4.2244	2.9511	5.4918	4.1264	3.2317
	Acpt. Wage				8.2292	6.6097	5.3363	8.3358	6.9704	6.0757
	Acpt. Prob.				0.0863	0.1702	0.2902	0.1450	0.2344	0.3210
	Hazard Rate				0.0080	0.0106	0.0128	0.0097	0.0200	0.0088
	Drop Prob.				0.1708	0.2636	0.4188	0.3519	0.3509	0.3377
University	Reser. Wage				8.9854	6.4410	4.5151	16.1429	10.9485	7.6013
	Acpt. Wage				11.8294	9.2750	7.3492	20.5827	15.3882	12.0411
	Acpt. Prob.				0.0420	0.1030	0.2033	0.0264	0.0849	0.1805
	Hazard Rate				0.0037	0.0064	0.0089	0.0018	0.0036	0.0050
	Drop Prob.				0.0398	0.1154	0.2728	0.0146	0.0999	0.2158

*. Only the number of children is relevant in this model.

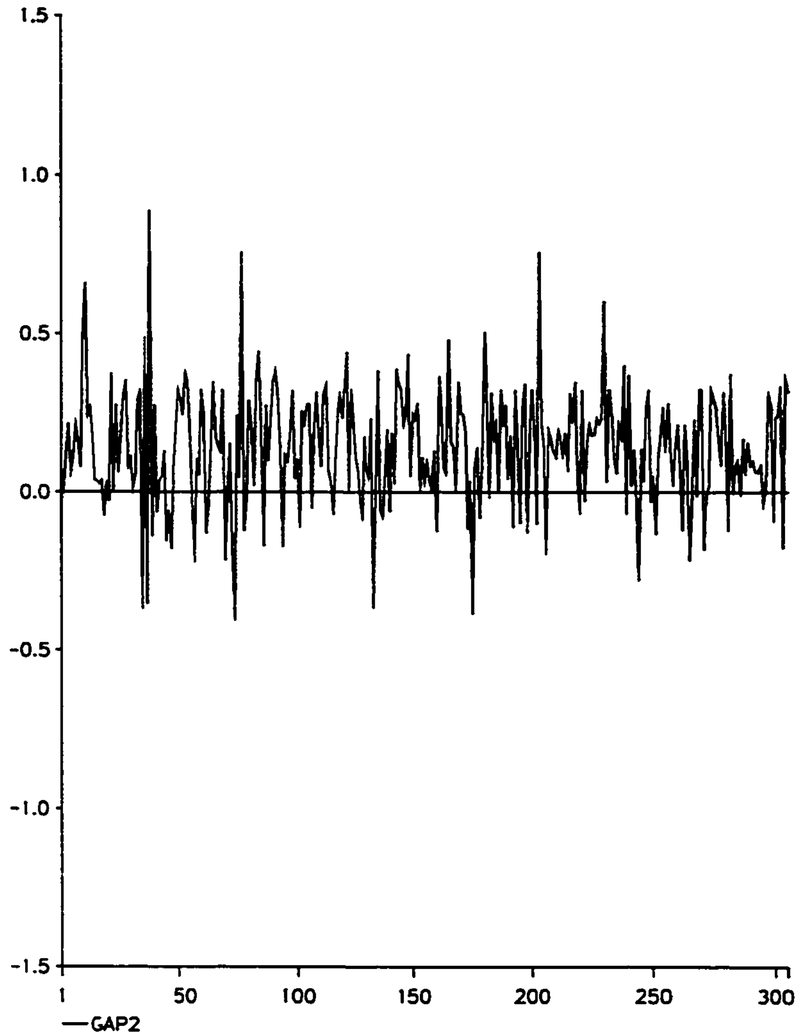
The distinction between married and single mothers is well illustrated in Tables 4.7 and 4.8. Table 4.7 contains the simulation results for the representative agent model. The table shows that single women have lower reservation wages than married women, regardless of child status. For women with no children, the acceptance probabilities, hazard rates and drop out probabilities are basically the same. For women with one or more children, married and single women are quite different in all the simulated items. Hence, we may conclude that married and single women behave similarly when they have no children, but differently when they have one or more children.

Figure 4.4: Gap between Predicted and Actual Wages: Parameterized Model I



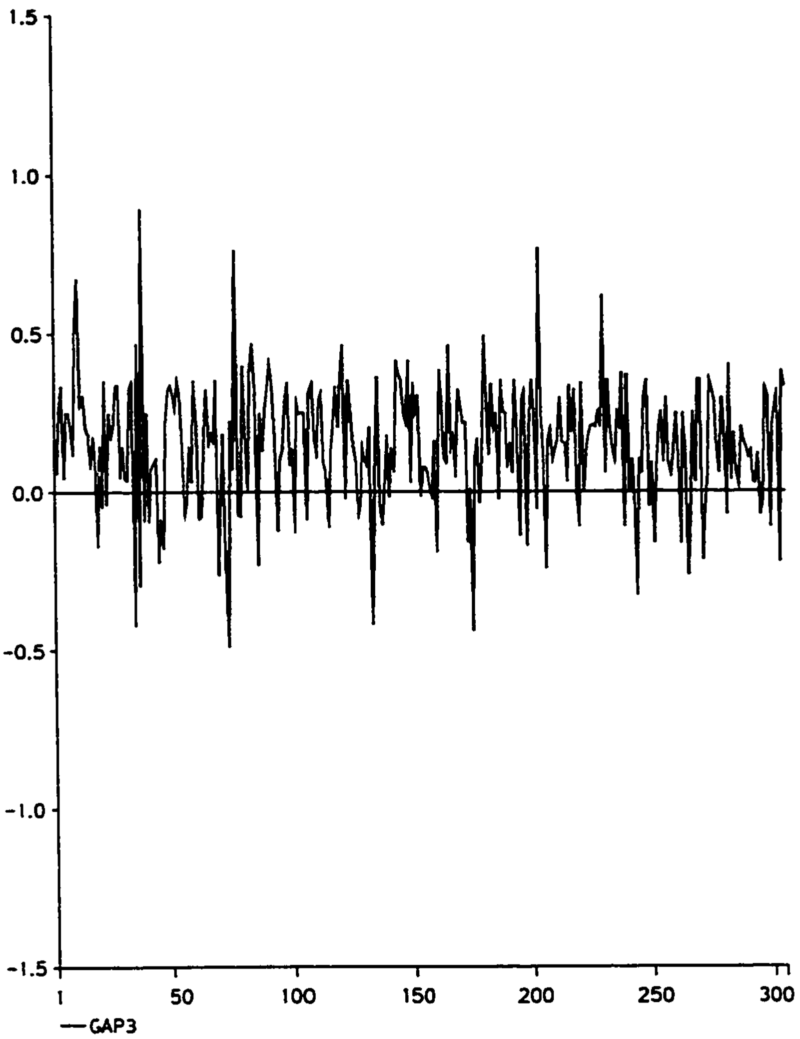
*. The prediction error is calculated as a percentage difference between expected and accepted wages. The vertical axis represents the percentage error while the horizontal axis represents the individuals who accepted a new job.

Figure 4.5: Gap between Predicted and Actual Wages: Parameterized Model II



*. The prediction error is calculated as a percentage difference between expected and accepted wages. The vertical axis represents the percentage error while the horizontal axis represents the individuals who accepted a new job.

Figure 4.6: Gap between Predicted and Actual Wages: Parameterized Model III



*. The prediction error is calculated as a percentage difference between expected and accepted wages. The vertical axis represents the percentage error while the horizontal axis represents the individuals who accepted a new job.

Table 4.7: Marital Status: Representative Agent Models

Marital Status	Married			Single		
Child Status	K=0	K=1	K=2	K=0	K=1	K=2
Reser. Wage	6.5390	4.8027	3.2264	5.3843	3.6603	1.9363
Acpt. Wage	9.6504	7.9941	6.3378	7.8281	6.1041	4.3801
Acpt. Prob.	0.1223	0.2082	0.3545	0.1104	0.2236	0.4528
Hazard Rate	0.0058	0.0099	0.0168	0.0053	0.0107	0.0216
Drop Prob.	0.0847	0.3291	0.8122	0.0729	0.2223	0.9548

Table 4.8 contains the simulations for the fully parameterized models. The estimation results of Section 4.4 are well illustrated by the simulations. Since single women with lower education have higher home productivity than their married counterparts, their drop out probabilities are very high and invariant with the number of children. But at higher educations, married women have higher home productivity and hence their drop out probabilities are higher than that of single women, and the drop out decision of married women seems affected more by child status. However, conditional on searching, single women are much less affected by child status at the higher education levels. Unfortunately, the finding that married and single women with no children behave similarly from the representative agent models is not supported by the simulations of the parameterized models.

Table 4.8: Simulations with Marital Status: Parameterized Models*

Marital Status		Married			Single		
Education	Child Status	K=0	K=1	K=2	K=0	K=1	K=2
Primary	Reser. Wage	3.1151	2.3450	1.7350	3.0914	2.1590	1.1538
	Acpt. Wage	4.8481	4.0779	3.4679	5.0532	4.0778	3.1157
	Acpt. Prob.	0.1657	0.2584	0.3674	0.2069	0.3401	0.5554
	Hazard Rate	0.0187	0.0188	0.0172	0.0125	0.0184	0.0269
	Drop Prob.	0.2434	0.3603	0.7058	0.6276	0.6857	0.7627
Secondary	Reser. Wage	5.8103	4.0817	2.8540	6.0128	4.7341	3.5002
	Acpt. Wage	8.0847	6.3561	5.1284	8.7330	7.4542	6.2204
	Acpt. Prob.	0.0777	0.1662	0.2851	0.1097	0.1755	0.2762
	Hazard Rate	0.0088	0.0121	0.0134	0.0066	0.0095	0.0134
	Drop Prob.	0.2305	0.4413	0.6448	0.1247	0.1989	0.4054
University	Reser. Wage	10.9982	7.4245	5.0080	8.5616	7.0183	5.5473
	Acpt. Wage	13.8930	10.3193	7.9028	11.7321	10.1888	8.7179
	Acpt. Prob.	0.0224	0.0769	0.1773	0.0672	0.1093	0.1738
	Hazard Rate	0.0025	0.0056	0.0083	0.0041	0.0059	0.0084
	Drop Prob.	0.0190	0.2228	0.5659	0.0290	0.0680	0.2542

*. Average hourly UI benefits are fixed at $1.8491.

4.6 Conclusion

It is generally recognized that young children have important effects on both the consumption and time allocation decisions of a household. In this chapter, we have analyzed an aspect which, to our knowledge, has so far been ignored; namely the impact of young children on the job search behavior of female displaced workers. In particular, we have examined two possible channels by which young children affect re-employment outcomes: the presence of child care costs and the possible reduction in the probability of receiving offers for those women who have young children and are therefore less effective at search activities.

The representative agent model indicates that women with young children are more likely to drop-out from the labor force (as expected) and those who search for a job absorb substantial child care costs while unemployed and therefore accept re-employment at lower wages than those who have no children. However, the parameterized version of the model, where offers are affected by the presence of young children, indicates quite clearly that child care costs are actually not incorporated in the determination of the optimal reservation wage and is therefore consistent with the claim that unemployment child care costs and re-employment child care costs are approximately equal. Instead, the presence of young children has a substantial (and significant) negative impact on the probability of receiving offers.

The results also indicate some differences between married and lone mothers. Lone mothers are more productive at home and drop out in larger numbers, but those who search are much less affected by young children than married women. Our estimates implied that lone mothers are unemployed for much shorter time periods than married mothers. Indeed, lone mothers with more than one child have the highest re-employment hazards of all groups.

As a result, both the representative agent model specification and the parametrized version of the model are consistent with the negative relationship between female wages and family size–a stylized fact observed in almost all western countries. This is interesting. If family size truly reduces the search effectiveness of young women and if we extend our results to job search activities while employed, then job search behavior can undoubtedly be a major factor in the persistence of a gender wage gap. We therefore suggest that some effort should be devoted to modelling the gender wage gap jointly with job search activities along with other forms of human capital investments.

Chapter 5

A Structural Model of the Gender Wage Gap

5.1 Introduction

For several decades, labor economists have tried to explain the existence of the gender wage gap. In most western countries, as women have constantly increased their share of the labor force, the interest in the persistence of a significant difference in wages paid to female versus male workers (given identical observable characteristics) has also grown. Recent work on the issue includes Blau and Kahn (1992, 1994), Light and Ureta (1995), O'Neill and Polachek (1993) and Kim and Polachek (1994). To date, economists have retained two fundamental economic frameworks to understand the gender wage gap: human capital theory and statistical discrimination.

In the human capital approach (which dates back to Mincer and Polachek, 1974), the gender wage gap is explained by the fact that females are relatively more productive in household activities than males. For this reason, they tend to invest less in labor market oriented human capital or tend to work in occupations which do not require heavy human capital investments. The gender wage gap is therefore the result of discontinuous work pattern expectations.

The literature on discrimination has, on the other hand, focused on the differential treatments toward otherwise identical male and females workers. The notion of discrimination, dating back to Becker (1971), is based on the fact that employers, facing uncertainty about individual productivity or individual labor force attachment, must often focus on observed differences between groups (males and females) when hiring new workers. As a result, women may systematically receive lower wages or may be excluded from various occupations (see Lundberg and Startz, 1983, for an example).

The approach to the gender wage gap suggested in this thesis is quite different from all previous work mentioned and has, to our knowledge, never been pursued before[1]. In this chapter, we investigate the gender differences in outcomes of job search that take place following a permanent job displacement. We analyze a sample of young males and females taken from the Canadian Labour Market Activity Survey and use the structural job search model developed in Chapter 2 to investigate their search behavior. With the distinct features of our theoretical model and a relatively large number of regressors for the structural parameters, including value of non-market time, mean wage offer, offer probability and search cost (which is rarely analyzed in the empirical literature), we are able to treat the reservation wage as a function of unknown parameters and exogenous regressors. Consequently, unlike most other empirical job search models, we do not impose the homogeneity across individuals over their optimality condition of job search.

We believe that the investigation of the gender wage gap using a structural model is particularly promising. First, the imposition of all the restrictions implied by the dynamic programming allows us to obtain separate estimates for all parameters of the mean wage offer and the reservation wage function. This means that we can actually compute how various regressors, such as the number of young children, marital status, education and the search parameters (including the probability of receiving offers and search costs) impact on males and females differently. Notably, this can be achieved without having to impose exclusion restrictions such as those

[1]However, Swaim and Podgursky (1994) have investigated, in a reduced-form framework, the unemployment duration of females after a permanent job displacement while Crossley, Jones and Kuhn (1994) have investigated how the effects of job displacement can differ across males and females.

needed in reduced-form analysis of female wage functions. In other words, our model allows us to distinguish between supply side versus demand side factors affecting the gender wage gap. Secondly, the tightness of the search problem has implications for the escape rate out of unemployment and the probability of dropping out of the labor force (because we actually estimate a search model with an endogenous decision to search). Our structural estimates can therefore be used to investigate gender differences in reservation wages, re-employment wages, unemployment duration and on the incidence of non-participation upon job displacement.

The likelihood function is based on information about the decision to search or not to search upon displacement, duration data and re-employment wage data. At a further stage, we also use information on the presence of young children to explain gender differences in job search behavior. In the next section, the econometric model and the estimation issues will be discussed. We then present the empirical results in Section 3. Section 4 investigates numerically the gender wage gap. The last section contains our concluding remarks.

5.2 The Model and its Estimation

To investigate the gender difference in job search outcomes (the wage gap in particular), the theoretical search model developed in Chapter 2 is applied to both male and female workers (full-time) who are affected by a permanent job displacement. Temporary layoffs are disregarded in the sample. In order to concentrate on issues related to the gender wage gap, two restrictions are imposed on the model. Specifically, since the approach adopted here is through studying the search behavior of the displaced workers and the economic environment faced by these workers, the cost of employment is assumed to be 0. It is also assumed that the cost of job search while unemployed is non-negative. This assumption is consistent with the empirical results of Chapters 3 and 4. This restriction intends to make sure that the relevant item in the value function does represent a cost measure to job seekers.

Given these and the assumptions made in Chapter 2, it is straightforward to derive the value functions associated with each labor market state (the value function for non-participation remains the same as in Chapter 2).

$$V_e(w) = \frac{w}{1-\beta} \tag{5.1}$$

$$V_u = b - \Psi + \beta \int_0^\infty V(w')\,dF(w) = b - \Gamma_u + \beta\, E[V] \tag{5.2}$$

$$V_n = \frac{1}{1-\beta}(\frac{1}{\tau}\exp(\tau K)) \tag{5.3}$$

Hence, the optimality condition is given by,

$$w^* = b - \Psi + \frac{\beta\delta}{(1-\beta)\lambda}\exp(-\lambda w^*) \tag{5.4}$$

where w^* denotes the re-employment reservation wage (for those who decide to search and remain in the labor force) . In addition, the necessary and sufficient condition of labor market participation is

$$\frac{1}{1-\beta}\left(\frac{1}{\tau}\exp(\tau K)\right) \leq b - \Psi + \beta E[V] = \frac{w^*}{1-\beta} \tag{5.5}$$

To take into account individual unobserved heterogeneity in the value of non-market time, we again introduce the stochastic element α that follows a normal distribution with mean 0 and variance σ^2 into the value function of non-participation. Combining the participation decision and the censoring information of unemployment spells, the likelihood function can be easily derived. While the functional form of the likelihood is the same as that in Chapters 2 and 3, the parameters to be estimated here are σ^2, the variance of α, home productivity parameter τ, offer arrival rate δ, wage distribution parameter λ, and the search cost Ψ. With the discount rate being assumed as a constant, we are able to identify all of the above structural parameters using the estimation strategy adopted in Chapters 2 and 3.

In order to introduce observed heterogeneity, we shall also generalize the model to incorporate parametrization of the offer probability, search cost parameter, the parameter representing home productivity and the mean wage offer . We shall also allow the offer probability to depend on child status. This might be relevant if for instance, those women with young children searching for a new job are less flexible or have less time to devote to search activities. To take this into account, we shall use the specification for offer probability as

$$\delta = \exp(\delta_{cons} + \delta_k K + \delta_{prim}\text{PRIM} + \delta_{univ}\text{UNIV} + \delta_{male}\text{SEX})$$

where PRIM=1 if the individual received primary or high school education and 0 otherwise, and UNIV=1 if the individual received university education and 0 otherwise. Both δ_{cons} and δ_k are negative parameters.[2] Similar arguments can be applied to gender differentials in search costs. In order to preserve positiveness of the search costs, we specify Ψ as a Γ–function of a constant and the indicator for child status $I(K > 0)$.

$$\Psi = \Gamma[\gamma_{cons} + \gamma_1 I(K > 0) + \gamma_{male}\text{SEX}] - 0.886$$

Since the gamma function has a minimum of 0.886, we subtract this amount to allow for the 0 search cost possibility.

A representative agent model can also be criticized for ignoring the fact that job seekers with different levels of education (human capital) do not search from the same distribution. In standard regression analysis of earnings (or log earnings), the number of regressors included is usually large. Given that LMAS does not have detailed age and schooling variables, we shall incorporate all the relevant information that allows us to control for individual endowments in human capital. We parameterize the offer distribution as a function of education binary variables (PRIM, UNIV are dummy variables indicating the highest level attained by an individual, individuals with secondary education are the reference group) and occupation categories: white collar (reference group), blue collar (BLUE) and professional (PROF), with those employed in farming related occupations being excluded from the sample. As our objective is to estimate the structural parameters of the effects of young children on search costs and reservation wages, we do not give a structural interpretation of the

[2]Of course, it is impossible to distinguish this hypothesis from the hypothesis that employers are less likely to offer employment opportunities to females with children.

regressors included in the mean wage offer equation

$$\lambda = \exp(\lambda_{cons} + \lambda_{prim}\text{PRIM} + \lambda_{univ}\text{UNIV} + \lambda_{prof}\text{PROF} + \lambda_{blue}\text{BLUE} + \lambda_{male}\text{SEX})$$

Finally, in some cases, we implement versions of the model where education also affects the productivity at home. So we specify the parameter representing the value of non-market time as the following

$$\tau = \exp(\tau_{cons} + \tau_{prim}\text{PRIM} + \tau_{univ}\text{UNIV} + \tau_{male}\text{SEX})$$

to capture the effect of education on home productivity.

5.3 Empirical Results

The empirical results are grouped in three sub-sections. We first present estimates of the structural models obtained separately for males and females, followed by the pooled estimation results. The pooled estimates are obtained by taking into account the observed heterogeneity and allowing parameters to differ between males and females. Finally, we present separate estimates by gender in order to illustrate how the presence of young children affects search outcomes of males and females differently.

5.3.1 Representative Agent Model by Gender

As a first step, we estimated a representative agent version of the model for males and females separately. The results are in Table 5.1. Since the model is specified under the assumption that the presence of young children only affects the value of non-market time, neither search costs nor the offer probability are allowed to depend on child status. The results reveal some interesting differences between males and females; there is a much more significant level of heterogeneity in the value of non market time among women than among men, women face much higher search costs (\$2.88 versus \$1.83) and women receive offers much less frequently than males (the probability of receiving an offer is 0.047 per week for females while it is .144 for males).

Interestingly, the difference between the mean wage offer for males and females is very small; \$3.65 for males and \$3.42 for females. This implies a gender wage gap of 6.7% in mean wage offers. However, because females seem to face higher search costs and receive offers less frequently, their discounted expected lifetime earnings will clearly be lower and so will their reservation wages.

Table 5.1: Representative Agent Model by Gender

Group	Male		Female	
Parameter	Coefficient	Asy. t-ratio	Coefficient	Asy. t-ratio
Unobs. Heterogeneity (σ)	5.0474	0.8378	3.6400	2.5834
Home Productivity (τ)	0.2625	0.3222	0.3785	1.7140
Search Cost (Ψ)	1.8277	1.0232	2.8818	2.5705
Arrival Rate (δ)	0.1443	2.6446	0.0466	4.5242
Wage Offer (λ)	0.2740	7.9576	0.2921	8.9835
Log Likelihood	-640.656		-1014.58	
Sample Size	494		794	

5.3.2 Pooled Estimates

As the estimates of Table 5.1 suggest that males and females might face different parameters, it is natural to pool males and females and investigate more precisely which of the parameters are more likely to explain male/female differences in wages. Our estimates of the wage gender gap can be improved substantially by incorporating observed heterogeneity, especially human capital variables affecting the wage offer distribution. In what follows, we consider two options. First, we analyze a model where wage offers are allowed to depend on gender (given education, occupation and industry).[3] A second option is to restrict wage offers to be independent of gender. This specification implies that gender differences in reservation wages (and therefore in accepted wages) can only be explained by gender differences in search parameters such as search costs, offer arrival rate and the value of non-market time.

[3]The gender gap in wage offers (given human capital) could be explained by discrimination or unobserved heterogeneity correlated with gender. However, we choose not to investigate the reasons why offers may differ.

Table 5.2: Gender Differences: Pooled Estimate

Model	Model I		Model II	
Parameter	Coefficient	Asy. t-ratio	Coefficient	Asy. t-ratio
σ	4.3260	6.0065	4.0220	11.3991
$\tau_{constant}$	-0.9167	-2.4354	-0.6773	-5.15859
$\tau_{primary}$	0.3172	0.5331	0.0232	.056164
$\tau_{university}$	-0.8315	-2.1705	-0.5640	-1.54820
τ_{male}	-0.2677	-0.8763	0.0431	.158239
$\gamma_{constant}$	5.5653	3.7983	2.4847	2.34969
γ_{male}	–	–	0.1507	.129625
$\delta_{constant}$	-3.4729	-10.8164	-4.5375	-25.1968
$\delta_{primary}$	1.2912	1.9587	1.5967	3.20729
$\delta_{university}$	1.6824	3.5355	-1.0826	-4.79232
δ_{male}	0.7502	2.2945	1.0641	6.50418
$\lambda_{constant}$	-1.3290	-10.8331	-1.7417	-16.7908
$\lambda_{primary}$	0.7367	4.8445	1.0184	6.77014
$\lambda_{university}$	0.2978	2.2526	-0.9269	-3.31537
$\lambda_{professional}$	-0.3806	-16.2812	0.2722	2.04310
$\lambda_{blue-collar}$	0.2152	11.7093	0.2556	3.02893
λ_{male}	-0.2784	-2.8777	–	–
Log Likelihood	-1264.66	–	-1277.39	–

Under Model I in Table 5.2, we present estimates obtained when the mean wage offer, the value of non-market time and the offer probability (λ, τ and δ) are functions of a gender binary variable (1 for male and 0 for female) and where both τ, λ and δ are allowed to be functions of education classes (primary, secondary–the reference group–and university). To restrict the number of parameters, we imposed homogenous search costs. The occupation dummies are incorporated in λ. In the second column, we present estimates for the parameterization which differs only in that wage offers are independent of gender (given education and occupation) while search costs are allowed to differ according to gender.

In order to illustrate the effects of education and gender on home productivity, we report below the computed value of non-market time for Model I. Overall, the value of non-market time is higher for individuals with university training and higher for those who have one young child. This is true for males as well as females. Interestingly, males are found to be more productive at home (on average) than females and wage offers are significantly higher for males than for females (λ_{male}=-0.2784).

Gender	Children	Primary	Secondary	University
	K=0	2.3800	3.2690	7.5075
Male	K=1	3.6232	4.4388	8.5772
	K=2	5.5149	6.0273	9.7992
	K=0	1.8212	2.5013	6.7981
Female	K=1	3.1537	3.7307	6.8362
	K=2	5.4612	5.5644	8.1362

The estimates found under Model II in Table 5.2 indicate that there is practically no difference in search costs between males and females (γ_{male} is 0.15 and insignificant). The gamma function specification implies that search costs are estimated to be equal to \$1.49 per hour (in column 1), \$1.32 for females and \$1.47 for males (in column 2).

The estimates of Model II also corroborate the fact that females receive offers at a much lower frequency than males. In this specification, wage offers are actually independent of gender so the only potential difference in productivity is in home production. The computed values for home productivity are illustrated below. Again, we observe that those individuals with a university background are more productive at home (whether male or female) but, in this specification, females are actually more productive at home than males. The estimates for the gender difference in offer probabilities (1.0641) reveal again that males have a much higher value of search.

Gender	Children	Primary	Secondary	University
	K=0	1.8423	1.8854	3.3146
Male	K=1	3.1703	3.2044	4.4818
	K=2	5.4554	5.4462	6.6061
	K=0	1.9234	1.9685	3.4601
Female	K=1	3.2350	3.2716	4.6197
	K=2	5.4408	5.4373	6.1677

Overall, the estimates of Table 5.2 are consistent with the existence of a significant gender wage gap. This is true whether wage offers are allowed to be dependent on gender (column 1) or not (column 2), although, in the specification of column 1, gender differences in reservation wages are partly explained by the differences in wage offers. At this stage, a natural step to undertake is therefore to parameterize our model so that search costs and offer probabilities are allowed to depend on child status.

5.3.3 Children and Job Search Outcomes

The last set of estimates presented are those obtained when we investigate how the presence of young children affect male/female search behaviour. We consider the cases where search costs and offer probabilities are parameterized as a function of the number of young children and compare estimates obtained for males and females separately.

The results (found in Tables 5.3 and 5.4) are quite explicit about gender differences and the presence of young children. First, we note that the value of non-market time is significantly different for females with university training (a very plausible result) while, for males, non-market time seems independent of education. More importantly, the probability of receiving a job offer is significantly lower for females with children (-.4071 in column 1 and -1.0248 in column 3). This implies that females with children face a lower value of search than females with no children or males and that, as a consequence, the optimal reservation wage is also lowered by the presence of young children. Interestingly, women with young children do not face significantly higher search costs; the estimates indicate that females without children face search costs of the order of \$1.20 per hour while those with children face search costs of the order of \$1.35 per hour. However, as pointed out in the previous chapter, this might be explained by the approximate equality of child care costs while employed and while unemployed.

Table 5.3: The Effects of Children for Males (N=494)

Model	Model I		Model II		Model III	
Parameter	Coef.	Asy. t	Coef.	Asy. t	Coef.	Asy. t
σ	5.2699	1.2378	5.3956	1.2347	4.2850	1.84309
$\tau_{constant}$	-1.1241	-0.4685	-1.1373	-0.4652	-1.5987	-1.8846
$\tau_{primary}$	-0.0779	-0.0698	-0.0444	-0.0426	0.4575	0.7123
$\tau_{universt}$	0.2581	0.1420	0.2420	0.1459	-0.29072	-0.2240
$\gamma_{constant}$	2.2836	1.0599	1.6656	0.2036	1.6414	0.2212
γ_{child}	–	–	0.1255	0.0429	0.1550	0.0625
$\delta_{constant}$	-2.5834	-5.0481	-2.4251	-4.4452	-2.3750	-4.4602
$\delta_{primary}$	1.3292	1.3746	1.2860	1.2929	0.9816	1.0569
$\delta_{universt}$	0.6281	0.6040	0.5750	0.5358	1.1673	0.8318
δ_{child}	-0.0063	-0.0546	–	–	-0.1312	-1.5159
$\lambda_{constant}$	-1.5645	-9.5584	-1.5130	-8.8998	-1.5157	-8.8745
$\lambda_{primary}$	0.6930	2.9836	0.6680	2.8343	0.6973	3.1314
$\lambda_{universt}$	-0.0575	-0.1591	-0.0773	-0.2171	0.0098	0.0241
$\lambda_{profesnl}$	-0.2077	-2.5109	-0.2007	-2.5074	-0.2842	-4.7060
$\lambda_{bluecolr}$	0.1149	1.3856	0.1168	1.5213	0.1130	2.7643
Log L.	-556.603	–	-554.677	–	-550.465	–

5.4 Investigating the Fertility Wage Gap

In this section, we use the structural parameters obtained in the previous section to simulate the expected gender wage gap and the expected differences in observed wages between those who have and those who do not have young children; this difference is referred to as the fertility wage gap.

As a starting point, it is interesting to analyze how the structural parameters obtained for a representative agent specification will predict the gender wage gap (Table 5.5). In the representative agent model, parameters were estimated without any parameterization and regardless of the presence of young children. In order to obtain values for reservation wages and expected re-employment wages (E[w | w >

Table 5.4: The Effects of Children for Females (N=794)

Model	Model I		Model II		Model III	
Parameter	Coef.	Asy. t	Coef.	Asy. t	Coef.	Asy. t
σ	3.6602	4.2289	3.9316	4.1681	4.5988	4.7896
$\tau_{constant}$	-0.8374	-2.9381	-0.9498	-2.0942	-0.7785	-2.6897
$\tau_{primary}$	0.3416	1.3340	0.5733	1.4674	0.3396	0.5068
$\tau_{universt}$	-0.8509	-3.0454	-0.5449	-1.3059	-0.7299	-2.2169
$\gamma_{constant}$	2.5773	3.6704	2.3738	3.7008	2.2717	2.7855
γ_{child}	–	–	0.1527	0.5777	0.1522	0.3720
$\delta_{constant}$	-2.9019	-7.5269	-2.6526	-7.2511	-1.4648	-3.6603
$\delta_{primary}$	-0.2862	-0.4640	-0.7249	-1.1906	0.9483	1.2038
$\delta_{universt}$	1.0224	1.8176	0.8736	1.7560	-0.1024	-0.2426
δ_{child}	-0.4071	-5.3664	–	–	-1.0248	-10.1979
$\lambda_{constant}$	-1.0643	-6.6002	-1.1159	-8.9679	-0.7438	-6.8051
$\lambda_{primary}$	0.1900	0.7782	0.4310	2.2951	0.7993	4.7788
$\lambda_{universt}$	-0.0452	-0.2487	0.0823	0.5678	-0.4423	-3.7540
$\lambda_{profesnl}$	-0.1908	-8.0755	-0.2272	-10.6842	-0.6503	-27.1199
$\lambda_{bluecolr}$	0.3978	5.6227	0.6532	11.5735	0.4854	16.8980
Log L.	-821.923	–	-829.976	–	-802.820	–

Table 5.5: Gender Gap: Representative Agent Model

	Mean Offer	Reservation Wage	Expected Wage
Male	3.650	9.764	13.418
Female	3.425	6.219	9.644
Gender Gap	6.6%	36.31%	28.13%

w^*]), we fix the UI benefit to a certain level (namely \$2.58 per hour, the average level of benefits observed in the sample). In the model with observed heterogeneity, wage offers are allowed to differ according to education and occupation classes. We fix the class variables to some particular values (secondary for education and white collar in service industries for occupation) so that a gender wage gap can be computed. Of course, male/female differences change only marginally when class variables are changed but the choice of a reference group is purely arbitrary. The values obtained when wage offers were a function of gender are in Table 5.6, while Table 5.7 contains the calculation when wage offers are independent of gender.

Table 5.5 shows that the representative agent specification is characterized by a gender wage gap around 28%, despite a relatively small difference in the mean wage offers (the mean wage offer for males is only 6.6% higher than that for females). This gender wage gap may therefore largely be explained by gender differences in reservation wages. We note that the expected wage gap predicted by the representative agent model is remarkably close to the actual accepted wage gap (27.6%).[4] This gap is also shown in Figure 5.1.

[4]See Chapter 7 for sample description.

Table 5.6: Wage Offer as Function of Gender

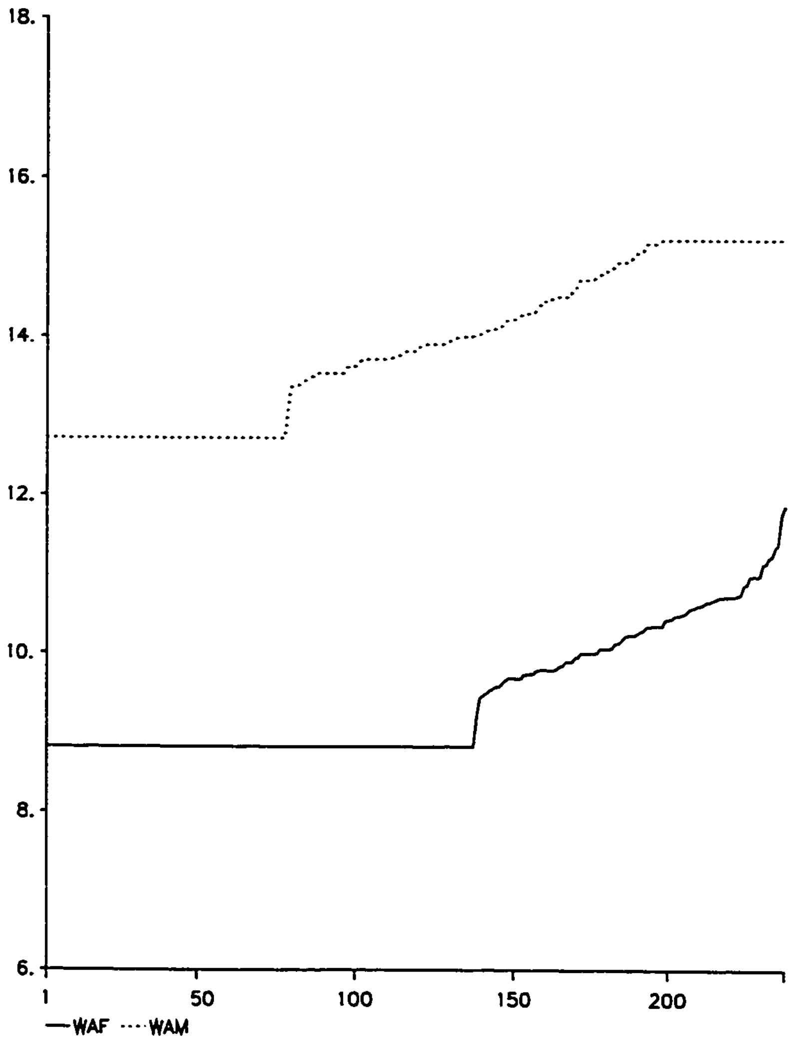
	Mean Offer	Reservation Wage	Expected Wage
Male	4.99	11.03	16.02
Female	3.88	6.84	10.62
Gender Gap	22.24%	37.99%	33.71%

Table 5.7: Wage Offer Independent of Gender

	Mean Offer	Reservation Wage	Expected Wage
Male	5.70	9.80	15.51
Female	5.70	6.77	12.46
Gender Gap	–	30.92%	19.67%

Table 5.6 contains the simulation results obtained from model specifications with observed heterogeneity, where gender enters into all but the search cost parameters. The results illustrate similar gender gap in terms of the reservation and expected wages, compared to the representative model. However, now one can see that females receive wage offers paying 22% less (after controlling for human capital). The second specification with observed heterogeneity (Table 5.7) is particularly interesting because it allows us to compute a gender wage gap which would prevail even when wage offers are independent of gender (but depend only on human capital). Despite identical mean wage offers, females have lower reservation wages (around 31% lower than males) and their accepted wages are 20% lower on average. This result is interesting. It means that a model with no gender discrimination in wage offers is consistent with a gender wage gap of the order of 20%. This gap is shown in Figure 5.2.

Figure 5.1: Wage Gap Predicted by Rep. Agent Model*

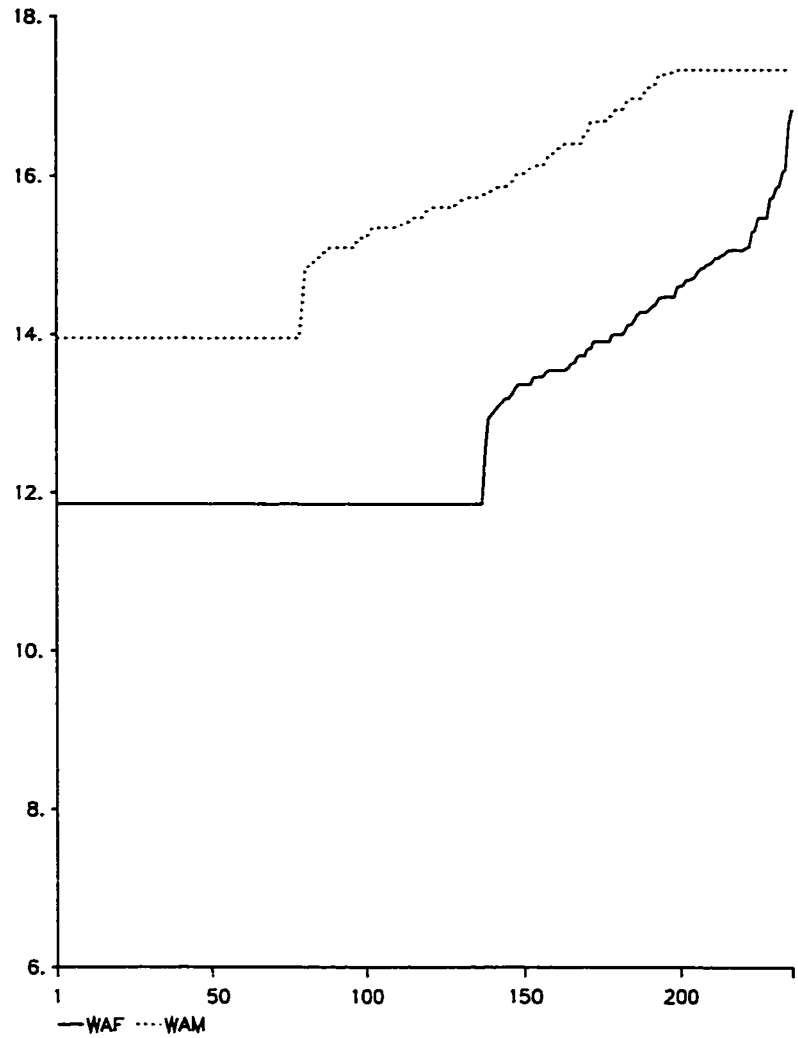


*. Solid curve (WAF) represents expected wage of female workers, dotted curve (WAM) stands for the expected wage of male workers. The vertical axis represents hourly wage rate ($), while the horizontal axis represents the individuals who accepted a new job.

As we stated while discussing the structural estimates (Tables 5.3 and 5.4), the presence of young children is a potential explanation for the difference between male and female reservation wages. Using the structural estimates obtained when we allowed both the offer probability and search costs to be function of child status, we can compute a wage differential attributed to the presence of young children (a fertility wage gap). We consider two cases: those with no children and those with one young child, and compare these two groups among males and females. These estimates will tell us the effects of young children on reservation wages and accepted wages for both males and females and can explain how much of the gender wage gap can be explained by the presence of young children.

The reservation wage and accepted wage calculated for males (Table 5.8) indicate that the presence of young children has virtually no impact on the accepted and reservation wages of males. This was already noted from Table 5.3. There only exists a difference of 2.5% in accepted wages for males with one child and males with no children. For females, the results are entirely different. Females with one young child have reservation wages 23% percent lower than those with no children and earn 17% less. This difference, when compared with the estimated gender wage gap of Tables 5.6 and 5.7 (34% and 20% respectively), points to the importance of young children in explaining re-employment outcomes for unemployed females. Using the expected re-employment wages for males with one child ($15.48), we see that females with one child earn around 28.36% less than males ($11.09) while females with no children earn 13.63% less ($13.37). Given that there exist virtually no differences between males with and without children, this implies that around 50% of the gender wage gap in observed re-employment wages can be explained by lower re-employment reservation wages of females with young children. Figure 5.3 graphically isolates the proportion of gender wage that can be explained by the presence of young children.

Figure 5.2: Wage Gap Unexplained by Gender*



*. Solid curve (WAF) represents expected wage of female workers, Dotted curve (WAM) stands for the expected wage of male workers. The vertical axis represents hourly wage rate ($), while the horizontal axis represents the individuals who accepted a new job.

Table 5.8: Fertility Wage Gap: Male

	Mean Offer	Reservation Wage	Expected Wage
K=0	4.55	11.33	15.88
K=1	4.55	10.93	15.48
Gender Gap	-	3.53%	2.52%

Table 5.9: Fertility Wage Gap: Female

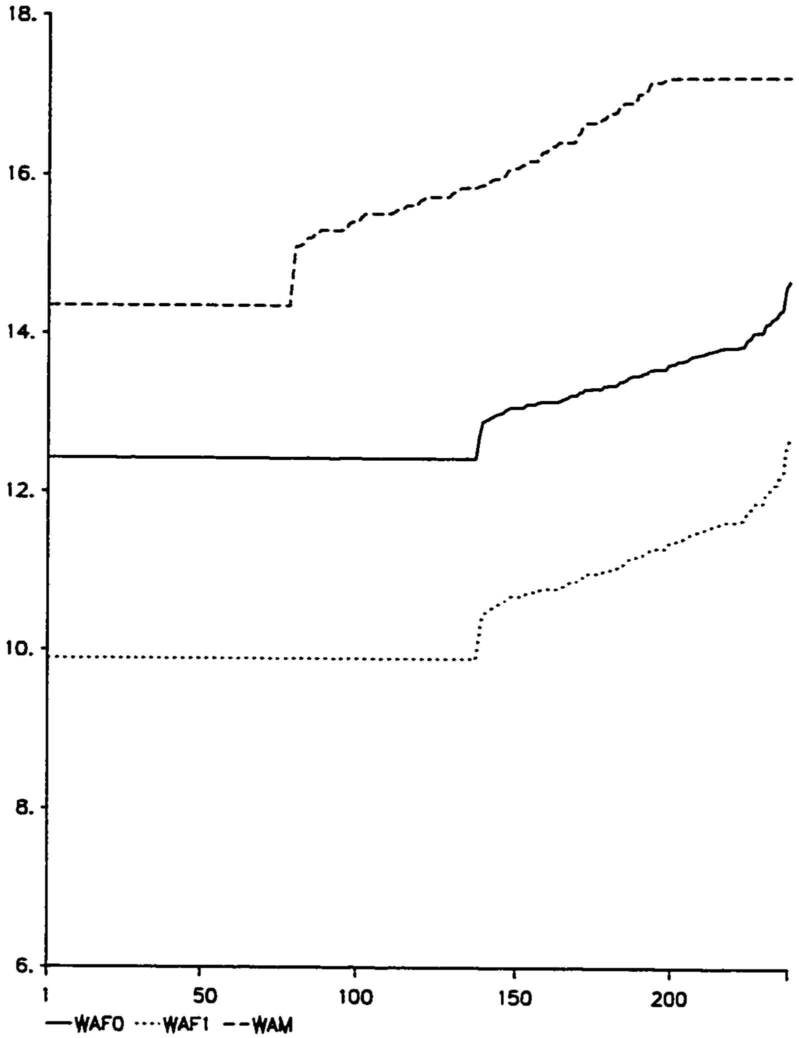
	Mean Offer	Reservation Wage	Expected Wage
K=0	3.27	10.10	13.37
K=1	3.27	7.82	11.09
Gender Gap	-	22.57%	17.05 %

5.5 Concluding Remarks

The fact that males tend to earn more than females is a stylized fact present in all industrialized countries. Several explanations, reviewed in the introduction section, have been proposed by labor economists. In this paper, we have proposed a new approach to the issue; namely, we have investigated how the job search process may differ across males and females. Using a structural job search model with endogenous search, we have estimated how differences in structural parameters can affect the discounted expected lifetime earnings of unemployed females and found that the presence of young children plays an important role in the setting of the optimal reservation wage, although there is very little evidence that the value of non-market time of females is higher than that of males.

Our structural estimates imply that females with no young children face parameters almost identical to male workers and the simulated values for both reservation and accepted wages indicate that approximately half of the gender wage gap is accounted for by the effect of young children on the main job search parameters. In particular, mothers of young children who suffered a permanent job separation will typically receive wages more than 15% lower than those who do not have children.

Figure 5.3: Gender Wage Gap vs. Fertility Wage Gap



*. Solid curve: expected wage of females without children; doted curve: expected wage of females with one child; dashed curve: expected wage of males with or without children.

Our results are therefore consistent with the claim that the gender wage gap is typically small when males and females enter the labor market but tends to increase with age or experience.

Chapter 6

Summary and Conclusion

Search theory has been widely applied to analyze the labor market dynamics in the past two decades. However, the data requirements and the difficulties in estimating the structural parameters prevent economists being able to go very far. This can be seen from the fact that only a small number of empirical studies have fully implemented the restrictions implied by the theoretical model. Furthermore, these structural studies focus basically on the labor market behavior of male workers. One of the key aspects of labor market decisions is ignored by these studies, namely the participation decision of a worker upon job separation. It is usually assumed that all displaced workers will search for another job immediately, and treat the participation decision as exogenous.

This thesis develops a search model that takes the participation decisions of displaced workers as endogenous. The model has therefore three labor market states: re-employment, unemployment with job search, and non-participation. The model also incorporates the possible costs associated with each of the states, and allows for the costs to be asymmetric over different labor market states. By assuming a simple exponential distribution for wage offers, the model directly takes the observed heterogeneity into the optimality condition. The specification of the value function of non-participation is also novel, it allows us to capture the value of non-market time for an individual with or without children, and include the unobserved heterogeneity in the value of non-market time across individuals.

Although stylized, the model is informative. It is able to accurately describe a few aspects of the labor market behavior of displaced workers. Meanwhile, by introducing the participation decision, the estimation can be relatively easily done and more structural parameters of the search model can be identified, e.g., the discount rate.

The applications in this thesis demonstrate the implementation of the theoretical model on some interesting topics in labor economics. In Chapter 3, we implement the model on a sample of young Canadians who had suffered a permanent job displacement during 1986. We have compared the empirical results of the three-state model with the standard two-state model and found that the two-state model might overestimate the effects of unemployment insurance benefits on a worker's reservation wage and escape rate of unemployment. We also found that the prediction gap between the expected and actually accepted wages produced by a simple representative agent three-state model is on average smaller than that produced by a corresponding two-state model.

The model is applied to study the effect of child care costs on female displaced workers' behavior in Chapter 4, where we identify the channel through which the presence of young children may affect the labor market decision of the displaced female workers. In particular, our result indicates that the presence of young children does not affect the reservation wages of these workers through child care cost differentials between the employment and unemployment states in any significant way. Rather, the presence of young children affects the reservation wages and escape rates of the workers primarily through the offer probabilities. Behavioral difference between married and lone women is also investigated.

Chapter 5 studies the wage gender gap. To our knowledge, this is the first time the wage gender gap is studied by a structural search model. Our model can very accurately predict the wage gap between male and female workers. In addition, we found that, of the wage gap that cannot be explained by gender, about 50% can be explained by the presence of young children. Again, the channel through which the presence of young children affects the wage gap may be more likely on the offer arrival rate rather than the cost parameters.

Without taking the participation decision into consideration, the inferences made by previous empirical search models are potentially subject to self-selection bias. With respect to this, this thesis advances the structural studies of the labor market behavior of displaced workers a major step in the right direction. Given the fact that the primary achievements made by the previous empirical studies are on the effect of UI benefit provision, the applications presented in Chapters 4 and 5 represent very useful extensions to the search theory. Based on the current work, further studies on the following topics are desirable.

1. The thesis assumes that a displaced worker makes his/her participation decision immediately after a job separation. The empirical analysis treats a displaced worker as a labor force participant when either the worker found a new job, or was willing to work and was actually looking for a job after the displacement. A displaced worker is treated as a non-participant if the worker was not willing to work, or the worker was willing to but did not look for a job after the displacement. However, it is possible that, due to changes in the economic environment, a displaced worker who initially decides to search for a new job may decide to withdraw from the labor force later; and a displaced worker who initially decides to withdraw from the labor force may decide to start search for a new job. An extension addressing these possibilities may be done by subjecting the participation decision of a displaced worker to an independently and identically distributed (i.i.d.) random shock in each non-employment (i.e. non-participation or unemployed search) period. Then, in determining the contribution of a non-employed individual to the likelihood function, one does not rely on the report made by the person but on the probability the person is searching, or dropping out. This extension will be done shortly.

2. A direct measure of the UI benefits received by a displaced worker is not available in the LMAS. Even though the author is very careful in coding the UI benefits for the displaced workers, the data might not be as accurate as expected. To deal with the measurement error in UI benefit data, the author suggests the introduction of a random error term into the value function of the

unemployment state. The error term may be assumed to have only two or three mass points to capture the unobserved heterogeneity in UI benefits.

3. For an unemployed worker who decides to search for a new job, the search activities may not be as time consuming as a full-time job. He/she is thus able to devote a certain amount of time for home production while searching for a job. Given the assumption (Chapter 2) made on the home productivity of a non-participant($\frac{1}{\tau_1}\exp(\tau_1 K)$), it is interesting to see what portion of this value an unemployed worker may claim and how this claim may affect the reservation wage of this worker. This extension can be done by specifying the value function of an unemployed worker as

$$V_u = b + \varphi\frac{1}{\tau_1}\exp(\tau_1 K) + \beta E[V],$$

where $0 \leq \varphi \leq 1$, measuring the percentage of the non-market product an unemployed worker may claim.

4. In this thesis, it is assumed that job seekers draw wage offers from an exponential distribution and the random element of the non-market time follows a normal distribution. These assumptions simplify the estimation considerably. Estimating the model under different wage distributions and different distributions for the stochastic element of the non-market time has not been pursued. Although not all the distribution forms may apply for the wage distribution, the log-normal distribution is an immediate candidate. Investigation under this wage distribution is left for future study.

Chapter 7

Data Appendix

7.1 The Canadian Labour Market Activity Survey

From 1978 to 1981, and from 1983 to 1985, Statistics Canada conducted the Annual Work Patterns Survey (AWPS) to provide information on the length and timing of employment and unemployment spells in the Canadian labor force. This survey was designed to complement the stock estimates, obtained from the monthly Labor Force Survey (LFS), by providing flow estimates that are compatible and consistent with the LFS concepts and definitions. But the month-specific estimates of employment and unemployment produced by the AWPS have a high degree of error when compared to the monthly LFS.

In 1986. the Canadian Labor Market Activity Survey (LMAS)[1] was designed as a replacement for the AWPS. The data was collected by Statistics Canada with the cooperation of the then Employment and Immigration Canada. The primary objectives of the LMAS are (1) to provide measures of the dynamic nature of the Canadian labor market which are conceptually consistent with the LFS, and (2) to provide information on the characteristics of paid jobs which are not available from the LFS.

The LMAS collected information on the annual labor market activities of a

[1]For details, see the Labour Market Activity Survey 1986–87 Longitudinal File Microdata User's Guide, 1990, Special Surveys Group, Statistics Canada

stratified sample of Canadians aged 16 – 69, resident in the ten provinces [2] over a referred calendar year. Sufficient information was obtained to assign a labor force status of employment, unemployment (with search, or without search but willing to work), or not in the labor force to each week of a reference year for each person surveyed.

7.2 The Sample of Displaced Workers

Our sample is drawn from the 1986–87 longitudinal file. The sample consists of male and female non-student workers who experienced a permanent job displacement from his/her full-time position in 1986. Job displacement information is based on Question 34 of the LMAS: *what was the main reason for stopping work?* 26 reasons were listed. Reasons K (non–seasonal economic or business conditions), L (Company moving or going out of business), O (end of a temporary non-seasonal job), and M (dismissal by the employer) are corresponding to the notion of permanent job separation. A person is defined as a student and is excluded from the sample if he or she reported attending a school, college or university as a full-time student in any month during the year. This is based on Question 98 of the LMAS: *Did ... attend a school, college, or university as a full-time student at any time in 1986*? To be included in the sample, a person must have been holding a full-time, paid job before the displacement. The term full-time job we used is that of LMAS (i.e. an employee works at least 120 hours per month). In addition, if a worker experienced more than one job displacements, only the last job displacement is taken into the sample.

Given these restrictions, we obtained 1910 observations from the 1986–87 longitudinal file. Among them, 1091 are female workers and 819 are male workers. Since we are interested in young and prime-age workers, we kept those who were aged less than 45 in our sample. This reduces the sample to 1525 (545 males and 980 females)[3].

[2]In particular, residents of the Yukon, Northwest Territories, Indian Reserves, inmates of institutions, and full-time members of Canadian Armed Forces are excluded.

[3]A dozen observations that do not meet some basic data consistency criteria maybe because of recording or coding errors, e.g. negative employment durations or unemployment durations were also deleted.

The 980 female displaced workers formed our sample for Chapter 4. In our empirical work on the the basic three-state model and on the gender wage gap, we further exclude those who did not report his/her occupation, and those whose occupation were farming, fishing, hunting, or trapping related. As a result, the number of observations left is 1288 (794 females and 494 males).

7.3 Definitions of Variables

The following variables are employed in this thesis: sex, marital status, education, number of young children, hourly unemployment insurance, occupation, hourly wage rate paid on the job before the displacement, hourly wage rate of the new job (if applicable) after the displacement, duration of unemployment, unemployment spell censoring indicator, and the non-participation indicator.

1. Some Simple Variables[4]. The variable sex is defined to be 1 for male, 0 for female. Marital status is classified in three sub-groups in the LMAS: married (or cohabiting), single, and other. We classify marital status in two categories, married and not married (the latter includes single and other). No detailed education levels are given in the survey. The LMAS classifies education into the following 5 classes,

Education	Last Degree
1	None or Elementary
2	High School
3	Some Post-secondary
4	Post-secondary or diploma
5	University

We construct three education dummies from the LMAS. The first one is defined to include the first two classes, the second one corresponding to the third and the fourth classes, and the last one for university. In our sample, the number of young children of a displaced worker consists of his/her own children aged between 0 and 5

[4]The LMAS extracts these information from the monthly Labor Force Survey (LFS) Forms 03 and 05.

inclusive. The LMAS also records number of children between 0 and 2 and between 3 and 5 separately. We add the number of children from both ranges to get observations on the number of young children.

2. Wage Rate and UI Benefits. As usual, we use the hourly wage rate to measure compensation of the jobs prior to and after displacement. Hourly wage rate for a paid job is a derived variable in the LMAS. The derivation is based on LMAS questions 58–60 which provide hours worked per day, days worked per week, and weeks per month, total annual earnings for all jobs, and the duration (in weeks) of the job held. The hourly wage rate paid on the job prior to the displacement is necessary for us to re-build the unemployment insurance (UI) benefits, which is not directly available in the LMAS. We build the UI benefits according to the information provided in the LMAS and a "For Release" (86–35) from the then Employment and Immigration Canada, dated October 29, 1986.

First, we determine whether a displaced worker reported receiving UI benefits over the calendar year according to LMAS question 102: *did ... receive income from any of the following sources in 1986? – unemployment insurance benefits.* If the answer is no, we assign 0 to his/her UI benefits. We then look at the eligibility criteria for the UI benefit.[5] According to the Unemployment Insurance Act and the amendment made in October 1986, a worker who is laid off by his/her employer for economic reasons would be eligible for the UI benefit if he or she (1) worked a minimum of 10–14 weeks for the employer, and (2) earned at least $99 per week or worked at least 15 hours per week on the job. We set 10 weeks as the entrance requirement. If these two conditions are not met by a worker's response in LMAS, we again assign 0 to his/her UI benefits.

Second, for those who reported receiving UI benefits and passed the two eligibility criteria, we calculate their weekly earnings according to their hourly wage rates and reported hours worked per week. Their weekly insurable earnings are determined to be either $495 (the maximum weekly insurable earnings at the time) if their

[5]Since a worker could claim UI benefits in more than one unemployment spell during a calendar year, this is necessary to prevent the calculated UI benefits from being assigned to a non-target unemployment spell.

weekly earnings were higher than $495, or the actual earnings if that was lower than the maximum weekly insurable earnings. This ensures that the maximum weekly UI benefit a displaced worker may claim is $297.

Finally, the weekly UI benefit are calculated as 60% of the weekly insurable earnings. We use a worker's reported hours worked per week on the prior job to calculate his/her hourly UI benefits.

3. Censoring and Non-participation Indicators. In a survey, some of the failure time observations are always incomplete. The LMAS for each calendar year is conducted in the first few months of the next year. For example, data for 1986 was actually collected in January, February, and March 1987. At the end of a survey, there are cases where respondents have not escaped from one state to another. Hence, their occupied spells are treated as censored. In constructing the censoring indicator for unemployment duration data, we define an unemployment spell to be completed if the displaced worker found a new paid job. The opposite case is defined as a censored spell.

The LMAS also collects data on the willingness to work from displaced workers. For any non-employment period, the LMAS asks (questions 21 and 24) *did ... look for work at any time during this period?* and *did ... want a job at any time during this period?* The participation data is established from these willingness to work information of the displaced worker. Specifically, we define a displaced worker as a labor force participant if he/she either was working, or not working, but wanted to work and was actually looking for a job during the unemployment spell. A displaced worker is defined as a nonparticipant if the individual did not have a job, did not look for a job and did not want work.

4. Unemployment Duration. We measure unemployment duration in weeks. The unemployment state is defined as a state in which a displaced worker does not have a job but is willing to work and is actually looking for one. The length of this state is calculated as unemployment duration. In the LMAS, the starting and ending weeks of a job held by a worker are recorded.[6] For a worker who escaped

[6]Any particular week in a calendar year is assigned a number from the week started on Sunday,

from unemployment, we define unemployment duration as the difference obtained by subtracting the stop week of his/her last job from the starting week of the new job. For a worker who did not accept a job until the end of the survey, his/her unemployment duration is obtained by subtracting the stop week of the last job from the week he/she was last interviewed.

As documented by Jones and Riddell (1995), the exact nature of the spells between the two jobs (or that between the job termination week and the ending week of the survey for censored spells) is not very clear. Every individual is asked to report their weekly status (whether they are searching, not searching but willing to work or simply not available to work) so the post-displacement status is actually a complex sequence of states which, in many cases, might not be consistent with a stationary search model where individuals decide (upon displacement) to search or not. For example, there might be a week within the unemployment period that the worker did not look for work, or did not want work, then the whole unemployment span can not be, strictly speaking, classified as unemployment since it contains one week of non-participation according to the standard definition of labor market states. However, in order to make the estimation of the model simple, we rely on the information provided by individuals on the questions whether they wanted to work and actually looked for job during the non-employment spells.

5. Occupation Dummies. For each job held by a respondent, the LMAS questionnaire collected information on the kind of work done and the usual duties or responsibilities of the respondent. This information was used to assign an occupation code to each job using the 1980 version of Statistics Canada's Standard Industrial and Occupational Classifications. LMAS reported 50 different occupations. After excluding workers from farming, fishing, hunting, trapping and related occupations, we classified the workers into three occupation dummies: blue collar workers, clerical, and professional. Professionals include those who hold managerial, scientific, researching, educational, health care positions (LMAS codes 01–16). Clerical workers include bookkeeping, secretary, library positions (LMAS codes 17–28). Blue collar

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December 31, 1900 (week 1), so the first week of 1986 is the 4435th week and the first week of 1987 is the 4488th week.

workers consist of workers in food and beverage processing, machining, repairing, transport operations (LMAS codes 34–50).

7.4 Descriptive Statistics

The sample statistics are presented in three separate tables. Table 7.1 contains a description of the sample employed in Chapter 4, while Tables 7.3 and 7.2 provide the statistics for data employed in Chapters 3 and 5.

Table 7.1: Descriptive Statistics for Young Females: N=980

Variable	Mean	Std. Dev	Min.	Max.
Marital Status	0.5857	0.4929	0	1
Number of Young Children	0.2786	0.5901	0	4
Primary	0.0990	0.2988	0	1
Secondary	0.5806	0.4937	0	1
University	0.3204	0.4669	0	1
Professional	0.1704	0.3762	0	1
Clerk	0.6469	0.4782	0	1
Blue Collar	0.1864	0.3427	0	1
Previous Wage	6.5118	3.3483	0.44	42.50
Accepted Wage*	7.2477	3.9413	1.25	42.84
UI Benefit	1.8491	2.3022	0	7.92
Unemployment Duration	22.9980	16.1706	1	64.00
Censoring Indicator	0.3122	0.4637	0	1
Participation Indicator	0.9396	0.2385	0	1

* Among these 980 observations, 306 workers accepted new jobs.

Table 7.2: Descriptive Statistics for Young Males: N=494

Variable	Mean	Std. Dev	Min.	Max.
Marital Status	0.5992	0.4906	0	1
Number of Young Children	0.3765	0.6860	0	4
Primary	0.1174	0.3222	0	1
Secondary	0.6336	0.4823	0	1
University	0.2490	0.4329	0	1
Professional	0.1456	0.3532	0	1
Clerk	0.1842	0.3881	0	1
Blue Collar	0.6700	0.4707	0	1
Previous Wage	10.0923	4.7059	1.72	37.39
Accepted Wage*	9.6082	4.4419	0.46	25.00
UI Benefit	3.9212	3.0012	0	7.92
Unemployment Duration	20.5243	16.1730	1	60.00
Censoring Indicator	0.5041	0.5005	0	1
Participation Indicator	0.9575	0.2020	0	1

* Among these 494 observations, 249 workers accepted new jobs.

Table 7.3: Descriptive Statistics for Young Females: N=794

Variable	Mean	Std. Dev	Min.	Max.
Marital Status	0.5781	0.4942	0	1
Number of Young Children	0.3325	0.6315	0	4
Primary	0.07809	0.2685	0	1
Secondary	0.5982	0.4906	0	1
University	0.3237	0.4682	0	1
Professional	0.1663	0.3725	0	1
Clerk	0.6725	0.4696	0	1
Blue Collar	0.1612	0.3680	0	1
Previous Wage	6.2843	2.9577	0.44	42.50
Accepted Wage*	6.9574	3.1565	1.60	21.09
UI Benefit	1.7465	2.2376	0	7.92
Unemployment Duration	22.6373	16.2473	1	64.00
Censoring Indicator	0.3325	0.4714	0	1
Participation Indicator	0.9396	0.2385	0	1

* Among these 794 observations, 264 workers accepted new jobs.

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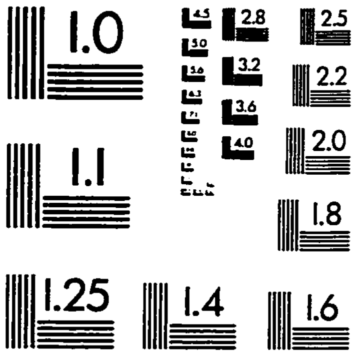
IMAGE EVALUATION TEST TARGET (QA-3)



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