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Labor market policies in an equilibrium matching model with heterogeneous agents and on-the-job search

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LABOR MARKET POLICIES IN AN EQUILIBRIUM MATCHING MODEL WITH HETEROGENOUS AGENTS AND ON-THE-JOB SEARCH

by

Olena Stavrunova

<u>An Abstract</u>

Of a thesis submitted in partial fulfillment of the
requirements for the Doctor of Philosophy
degree in Economics
in the Graduate College of
The University of Iowa

July 2007

Thesis Supervisor: Professor John Geweke

ABSTRACT

This dissertation quantitatively evaluates selected labor market policies in a search-matching model with skill heterogeneity where high-skilled workers can take temporary jobs with skill requirements below their skill levels. The joint posterior distribution of structural parameters of the theoretical model is obtained conditional on the data on labor markets histories of the NLSY79 respondents. The information on AFQT scores of individuals and the skill requirements of occupations is utilized to identify the skill levels of workers and complexity levels of jobs in the job-worker matches realized in the data. The model and the data are used to simulate the posterior distributions of impacts of labor market policies on the endogenous variables of interest to a policy-maker, including unemployment rates, durations and wages of low- and high-skilled workers. In particular, the effects of the following policies are analyzed: increase in proportion of high-skilled workers, subsidies for employing or hiring high- and low-skilled workers and increase in unemployment income.

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CERTIFICATE OF APPROVAL

PH.D. THESIS

This is to certify that the Ph.D. thesis of

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To my family.

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ABSTRACT

This dissertation quantitatively evaluates selected labor market policies in a search-matching model with skill heterogeneity where high-skilled workers can take temporary jobs with skill requirements below their skill levels. The joint posterior distribution of structural parameters of the theoretical model is obtained conditional on the data on labor markets histories of the NLSY79 respondents. The information on AFQT scores of individuals and the skill requirements of occupations is utilized to identify the skill levels of workers and complexity levels of jobs in the job-worker matches realized in the data. The model and the data are used to simulate the posterior distributions of impacts of labor market policies on the endogenous variables of interest to a policy-maker, including unemployment rates, durations and wages of low- and high-skilled workers. In particular, the effects of the following policies are analyzed: increase in proportion of high-skilled workers, subsidies for employing or hiring high- and low-skilled workers and increase in unemployment income.

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CHAPTER 1

INTRODUCTION

Active labor market policies such as state-subsidized general and vocational training, hiring and employment subsidies are often used in order to improve labor market outcomes of less-skilled workers. These policies affect firms' and workers' decisions regarding vacancy creation, search effort, reservation match quality, etc. A comprehensive evaluation of these effects is required to assess the ability of proposed policies to affect wages and employment of the target skill group, as well as the potential impact of the policies on the labor markets for other skill groups. The equilibrium matching model in the spirit of Diamond (1982) and Mortensen and Pissarides (1994) with skill heterogeneity is a powerful tool for such an analysis. In my thesis I undertake a quantitative study of selected labor market policies in the search-matching model with heterogeneous jobs (simple and complex) and workers (high-skilled and low-skilled), where high-skilled workers take transitory jobs with skill requirement below their skill level and continue to search on-the-job for complex jobs. This set-up enriches the interactions between the labor markets for different skill groups compared to the standard matching model with skill heterogeneity, and is motivated by studies which document the existence of spill-overs of workers into jobs with skill requirement below their skill level both in US and Europe.

The received matching model with skill heterogeneity developed in Mortensen and Pissarides (1999) and Mortensen and Pissarides (2003) to study the impact of institutions and policies on labor market outcomes of workers of different skill levels assumes that markets for different skill levels are completely segregated: in equilibrium there is a perfect match between worker's skill level and job's skill requirement. However, Sattinger (1995) and Shimer and Smith (2000) show that in a market with search frictions agents might agree to match with jobs which are not of their most preferred type. One of the forms of the type mismatch in the labor market - workers taking stepping-stone jobs below their skill level - has received a lot of attention in recent literature. A number of studies document the existence of spill-overs of workers into jobs with skill requirement below their skill level in both US and Europe. Sicherman (1991) reports that in his sample of male heads of households drawn from 1976 and 1978 waves of PSID 40% of the workers report themselves as overeducated when asked: "How many years of education is required to get a job like yours?" This study finds that overeducated workers have higher earnings and are more likely to switch employers and to move to higher-level occupations compared to workers whose educational level exactly matches the requirements of their job. Hersch (1991) using a sample of employees drawn from eighteen establishments in Oregon in 1986, finds that 50% of workers have higher educational attainment than required by their current job. Overeducated workers in her sample have higher earnings than workers who are not overeducated, and are more likely to quit their current job. Dolado, Jansen, and Jimeno (2003) present some stylized facts about the overeducation in 13 countries of EU. They find that the percentage of workers with educational levels corresponding to the two highest categories (categories 5 and 6) of the International Standard

Classification of Education employed in a job with lower skill requirements than jobs corresponding to the worker's educational attainment ranges from 15% – 17% for Germany, UK and Sweden to 23% – 25% in Spain, Portugal, Greece, Italy. Their findings suggest a positive relationship between the degree of overeducation and the intensity of tertiary education in the 13 selected countries.

When high-skilled workers spill-over into the lower skill segment of the labor market, the predictions of the standard matching model with skill heterogeneity with respect to some policies might no longer hold. For example, suppose the policymaker intends to achieve a reduction in the low-skilled unemployment by introducing employment subsidies to firms employing low-skilled labor. In the standard Mortensen and Pissarides (2003) model with skill heterogeneity and segmented markets this policy will increase job creation, employment and wages in the low-skilled sector, and will have no effect on the high-skilled sector. However, if high-skilled workers agree to match with jobs below their skill level, they will spill-over into the new jobs in the lower skill segment of the labor market, thus undermining the conclusions of the model regarding the effectiveness of the policy in reducing low-skilled unemployment.

Another consequence of the perfect segregation of markets for different skill levels in the textbook matching model is its inability to address the effects of changes in skill composition of the labor force, potentially induced by training programs, on job creation, employment and wages in markets for different skill groups. However, Acemoglu (1999) shows that when firms can not exclude workers who do not qualify from applying for jobs, the skill composition of the labor force becomes an important factor for firm's choice of a vacancy type in a labor market with matching frictions.

Recent papers by Albrecht and Vroman (2002), Gautier (2002), and Dolado, Jansen, and Jimeno (2003) develop matching models with heterogeneity, which can be used to evaluate labor market policies in the environment where workers spill-over into jobs with skill requirement below their skill level, and skill composition of the labor force affects firms' vacancy creation decisions. These papers share the assumptions about the heterogeneity of workers and firms: there are two types of jobs (simple and complex) and two types of workers (low-skilled and high-skilled). The key feature of these models is the assumption on the production technology: the matches between low-skilled worker and simple job, high-skilled worker and simple job and high-skilled worker and complex job are the only productive matches. Thus, low-skilled workers can be hired for simple jobs only, while high-skilled workers can be hired to perform both types of jobs. The skill composition of workers is exogenous, while the distribution of jobs is endogenous and is determined in equilibrium by the free entry conditions for firms. In these models job creation in the low-skill segment of the labor market can affect job creation in the high-skill segment, and vice versa. In Albrecht and Vroman (2002) mismatched high-skilled workers are not allowed to search on the job, therefore it is worthwhile for them to mismatch only when the productivity of complex job and/or the amount of complex vacancies are relatively low. This set-up gives rise to two equilibria: one in which markets for the two skills are completely segregated, and another in which high-skilled workers agree to take simple jobs. In the models of Gautier (2002) and Dolado, Jansen, and Jimeno (2003) on-the-job search is allowed for mismatched high-skilled workers, so that in equilibrium it is always optimal for unemployed high-skilled workers to accept simple jobs. Crucial for this result is the assumption made in both papers that mismatched high-skilled workers search on the job with the same efficiency as they do when unemployed.

In my thesis I undertake a quantitative study of selected labor market policies within the context of the matching model with skill heterogeneity and on-the-job search by mismatched high-skilled workers based on Dolado, Jansen, and Jimeno (2003). On-the-job search by mismatched high-skilled workers is consistent with the overeducation studies which find that overqualified workers have a higher propensity to quit than workers who are not overqualified. In the model the skill distribution of workers is exogenous and the complexity distribution of vacancies is endogenous, as ex-ante homogeneous firms decide what kind of vacancy to open, simple or complex. Simple jobs can be performed by skilled and unskilled workers, while complex jobs can be performed by skilled workers only. High-skilled workers take transitory simple jobs and continue to search on the job for higher-paying complex jobs. The number of meetings between vacancies and job-seekers is determined by the aggregate matching function. In equilibrium of the model employment and wages of the two skill groups are all functions of exogenous parameters such as non-employment income of workers, productivity of matches with different combinations of skill and complexity types, skill composition of the labor force, efficiency of the matching process, job destruction rates of simple and complex jobs and the cost of maintaining a vacancy. The attractive feature of this model for the analysis of labor market policies targeted at a particular skill group is that it can be used to to study potential feedback effects of such a policy on labor market outcomes of other skill groups.

To perform a quantitative study of selected policies I first develop a Bayesian procedure to obtain the joint posterior distribution of structural parameters of the model using the following data on labor market histories of respondents to the National Longitudinal Study of Youth 1979 (NLSY79): duration of non-employment spell between school completion and first full-time job, wage on the first full-time job and duration of the first full-time job. In addition to that I make a simultaneous use of the data on AFQT scores of individuals and on intelligence requirement of the occupation (IRO) on the first full-time job as estimated by Ingram and Neumann (2006) for 3-digit Census occupational codes to identify skill types of workers and complexity types of jobs. I specify that *on average* high-skilled individuals have higher AFQT scores than low-skilled individuals, and that *on average* complex occupations have higher IRO than simple occupations, but the skill type of a worker and the complexity type of a job in the realized matches in the data are imperfectly observed. Thus, the joint likelihood of durations, wages, AFQT scores and the IRO for any individual is a mixture over three latent states corresponding to the three types of matches between workers and jobs arising in a cross-skill matching equilibrium of the model. The posterior probability that a worker-job match is of a particular skill-complexity type is the function of the selected measures of skill and complexity, as well as of the length of unemployment and employment spells and wages, whose distributions over different skill and complexity types are specified by the model.

Next, the posterior distribution of structural parameters and the model are used to evaluate the posterior distributions of equilibrium effects of selected policies on wages, unemployment rates and durations of low- and high-skilled workers, as well as on other endogenous variables which may be of interest to a policy-maker. I study the impacts of the policies which include subsidies given to firms for hiring or keeping employed workers of low- and high-skilled groups, skill upgrading modeled as an increase in the share of high-skilled workers in the labor force, and increase in unemployment income. I also consider combinations of these policies in policy mixes with balanced government budget. These policy experiments amount to adding a fixed constant to an unknown structural parameter in each experiment. The uncertainty about all structural parameters translates into uncertainty about the quantitative predictions of the model with respect to effects of the policies on endogenous variables of interest. To account for this uncertainty I simulate policy impacts for a range of the structural parameters representative of their joint posterior distribution.

The rest of my analysis is organized as follows: chapter 2 presents the theoretical model with policy instruments, chapter 3 discusses inference, data and some properties of the joint posterior distribution of the structural parameters, chapter 4 discusses simulated policy effects, and chapter 5 concludes.

CHAPTER 2

THE MODEL

2.1 Assumptions

The model is set in continuous time. The economy is populated by a continuum of infinitely lived, risk-neutral workers with measure normalized to unity. The exogenous fraction $\mu \in (0,1)$ of the workers are low-skilled (l) and the remaining fraction, $1-\mu$ are high-skilled (h).

Firms choose to open one of two types of jobs: simple (s) or complex (c). The only productive matches between workers and firms are those between low-skilled workers and simple jobs, high-skilled workers and simple jobs, high-skilled workers and complex jobs. Therefore, low-skilled workers can be hired for simple jobs only, while high-skilled workers can be hired for simple and complex jobs. I assume that productivity of high-skilled worker on simple job can be different from productivity of low-skilled worker on simple job. Let $y_{i,j}$ denote a flow output from the match between a job of type i occupied by a worker of type j. Then the production technology of this economy can be summarized as follows:

$$y_{c,h} > y_{s,l} > y_{c,l} = 0$$

$$y_{c,h} > y_{s,h} > y_{c,l} = 0.$$

The firms can open at most one vacancy and the choice of a vacancy type is irreversible. The amount of vacancies of each type is determined by firms' free-entry conditions.

Workers can be unemployed and employed. While unemployed, a worker receives a flow income $b < \min\{y_{s,l}, y_{s,h}\}$. Jobs can be filled and vacant. A job of type j filled with a worker of type i produces a per-period output $y_{j,i}$. A vacant job does not produce any output, and a firm has to pay a cost of maintaining a vacancy κ equal for the two types of vacancies.

High-skilled workers occupying simple jobs are allowed to search on the job for complex jobs. Thus, the job seekers in this economy consist of three groups: unemployed low-skilled workers u_l, unemployed high-skilled workers u_h and high-skilled workers employed on simple jobs $e_{s,h}$. Job seekers and vacant jobs meet each other randomly, and the rate at which a job seeker meets a vacancy is determined by the aggregate meeting function $m(v_s + v_c, u_l + u_h + e_{s,h})$, which is assumed to be increasing and constant returns to scale in both arguments. First argument is the total number of vacancies $v_s + v_c$, where v_i denotes the mass of vacancies of type i. Second argument is the total number of job seekers $u_l + u_h + e_{s,h}$.

The search process is not directed: unemployed low-skilled workers can meet complex vacancies with which they will not match. Similarly, high-skilled workers employed on simple jobs and searching for complex vacancies can meet simple vacancies with which they will refuse to match. The undirected search captures the idea that low-skilled workers are better off when the number of simple vacancies is large, and that firms with complex vacancies are better off when the number of high-skilled job seekers is larger.

Jobs are created when unemployed low-skilled workers meet simple vacancies, when unemployed high-skilled workers meet simple or complex vacancies, and when high-skilled workers employed in simple jobs meet complex vacancies. To derive the rates with which meetings between job-seekers and vacancies result in a job match I first define the labor market tightness θ as the ratio of the number of vacancies to the number of job seekers:

$$\theta = \frac{(v_s + v_c)}{(u_l + u_h + e_{s,h})}.$$

Also, I define the following shares:

$$\phi = \frac{u_l}{(u_l + u_h)},$$

$$\psi = \frac{(u_l + u_h)}{u_l + u_h + e_{s,h}},$$

where ϕ is the fraction of unemployed workers who are low-skilled, and ψ is the fraction of job seekers who are unemployed. Then the proportion of unemployed workers who are high-skilled is equal to $1 - \phi$, and the proportion of job seekers who are high skilled unemployed workers is equal to $\psi(1 - \phi)$.

A firm meets a job-seeker at the rate equal to $q(\theta) \equiv \frac{m}{(v_s+v_c)} = m(1, \frac{1}{\theta})$. Because the search process is undirected, not every meeting between a vacancy and a worker produces a productive match. A meeting between a simple vacancy and a job seeker results in a match only when a simple vacancy meets unemployed low- or high-skilled worker. It is also possible that a simple vacancy meets a high-skilled mismatched job-seeker who will refuse to match. Therefore, the effective rate of matching of a simple vacancy with a job seeker is $\psi q(\theta)$. A simple vacancy matches with a low-skilled worker at the rate $\psi\phi q(\theta)$, and with the high-skilled worker at the rate $\psi(1 - \phi)q(\theta)$.

A meeting between a complex vacancy and a job seeker results in a productive match only when a complex vacancy meets a high-skilled worker. It is also possible that a complex vacancy meets a low-skilled unemployed worker with whom it will refuse to match. Therefore, the effective rate of matching of a complex vacancy with a worker is $(1-\psi\phi)q(\theta)$.

A job seeker meets a vacancy at the rate $\theta q(\theta) = \frac{m}{u_l+u_h+e_{s,h}}$. Let $\eta = \frac{v_s}{v_s+v_c}$ denote the share of simple vacancies in a mass of vacancies. An unemployed low-skilled worker becomes employed only when she meets a simple vacancy, thus the effective rate of exit from unemployment of a low-skilled worker is $\eta\theta q(\theta)$. High-skilled workers qualify for both types of jobs, and, as will be shown later, the assumption that high-skilled workers on simple jobs meet complex vacancies at the same rate as they do when unemployed guarantees that high-skilled workers will always accept low-skilled jobs when unemployed. Therefore, high-skilled unemployed workers exit unemployment at the rate $\theta q(\theta)$. High-skilled employed job seekers find employment in complex jobs at the rate $(1-\eta)\theta q(\theta)$.

The properties of the matching function imply that $q(\theta)$ is decreasing in θ and $\theta q(\theta)$ is increasing in θ. Thus, vacancies meet job seekers more frequently when the amount of vacancies relative to the amount of job seekers is low, and jobs seekers meet vacancies more frequently when the amount of vacancies relative to the amount of job seekers is high. Conventionally, I assume that $lim_{\theta\to\infty}q(\theta) = lim_{\theta\to 0}\theta q(\theta) = 0$ and $lim_{\theta\to 0}q(\theta) = lim_{\theta\to\infty}\theta q(\theta) = \infty$.

After a meeting between a job-seeker of type i and a vacancy of type j results in a match, the output $y_{j,i}$ is produced. I consider a cross-skill matching equilibrium, i.e. an equilibrium in which the tree types of matches is created: low-skilled workers with simple jobs, high-skilled workers with simple jobs and high-skilled workers with complex jobs. After the output produced in a match of a worker of type i and a job of type j is sold, the proceeds are split between a worker and a firm according to a wage rule defined in section 2.3. Matches between simple jobs and workers dissolve exogenously with rate δ_s. Matches between complex jobs and workers dissolve exogenously with rate δ_c. After a match between a worker and a firm is dissolved, a worker becomes unemployed and starts looking for a new employment opportunity, and a job becomes vacant.

2.2 Policy Instruments

Following Mortensen and Pissarides (2003) I introduce three policy instruments which can affect firms' vacancy creation decisions: one-time hiring subsidies H_l and H_h paid to the firm for hiring high- or low-skilled worker respectively; continuous employment lump-sum taxes or subsidies a_l and a_h paid to a firm per unit of time during which it employs low- or high-skilled worker respectively: a_j is positive if a policy instrument is a subsidy and negative if a policy instrument is a tax; one-time job destruction taxes F_l and F_h that are imposed on a firm when a match between a job and a low- or high-skilled worker respectively is destroyed.

2.3 Match Formation

The necessary conditions for match formation between a workers of type i and a job of type j depend on the values of matches to workers and firms and on the outside options of workers and firms. Let $W_{i,j}$ denote the present discounted value of the expected income stream of a worker of type j employed on a job of type i, and let U_j denotes the present discounted value of the expected income stream of unemployed worker of type j. $W_{i,j}$ is the value of a match with a job of type i to a worker of type j, and U_j is the outside option of a worker of type j. Let $J_{i,j}$ denote the present discounted value of expected profits from a job of type i filled by a worker of type j, which includes any taxes or subsidies applied to this match. Let V_i denote the present discounted value of expected profits from an unfilled vacancy of type i. $J_{i,j}$ is the value of a match with a worker of type j to a firm of type i, and V_i is the outside option of a firm of type i. In equilibrium the value of a match for a worker or a firm will depend on the wage paid to a worker. I assume that when a match between a worker of type j and a job of type i is consummated, the wage $w_{i,j}$ satisfies the linear surplus sharing rule: a wage that a worker of type j receives in a match with a firm of type i is set so that the worker receives a fixed exogenous share β of the total match surplus $S_{i,j}$. Following Mortensen and Pissarides (2003) the total surplus from the match between a worker of type j, $j \in \{l, h\}$ and a job of type i, $i \in \{s, c\}$ in the presence of policy instruments introduced in section 2.2 $S_{i,j}$ can be expressed:

$$S_{i,j} = W_{i,j} - U_i + J_{i,j} - V_j + H_j. \tag{2.1}$$

The joint surplus $S_{i,j}$ is a difference between the total gains from a match $W_{i,j} + J_{i,j} + H_j$ and the total gains from the alternative of continuing unmatched $U_i + V_j$. The total gains from a match are increased by the one-time hiring subsidy H_j beyond the sum of values $W_{i,j} + J_{i,j}$. [1] Thus, the linear surplus sharing rule implies that in a match between a worker of type j and a job of type i the wage $w_{i,j}$ is set so that the worker's surplus from the match $W_{i,j} - U_j$ is equal to the fixed fraction β of the total surplus $S_{i,j}$:

$$(W_{i,j} - U_j) = \beta(W_{i,j} - U_i + J_{i,j} - V_j + H_j), \tag{2.2}$$

where $\beta \in (0, 1)$. According to Binmore, Rubinstein, and Wolinsky (1986), this wage-setting rule can be motivated as the equilibrium outcome of a bargaining games in which the two parties to the match take turns at proposing how to split the match surplus. Similar assumption about the wage-setting mechanism in the search and matching models with on-the-job search have been made in Mortensen (1994), Pissarides (1994), Pissarides (2000) and Barlevy (2002). In the papers of Gautier (2002) and Shimer (2001) a simpler assumption about the wage-setting mechanism in the similar context in made. In these models a worker and an a firm split the per-period output of the match rather than divide the total match surplus.

[1] Pissarides (2000) observes that the choices facing the firm and the worker when they first meet are different from the choices the two parties face when the match is already established. In particular, the surplus from a filled job in a continuing match is $S_{i,j} = W_{i,j} - U_i + J_{i,j} - V_j + F_j$, because after the match is already established the firing tax F_j becomes operational. Therefore, if workers can renegotiate the initial wage, the two-tier wage structure may arise: the outside wage, obtained by the division of the surplus defined in (2.3), and the inside wage, obtained by the division of the surplus defined in this footnote. I abstract from this possibility here to simplify the analysis.

To make it worthwhile for a vacant job and a job seeker to match it must be the case that the gains from a match to both sides are at least as high as gains from the alternative of continuing unmatched. Thus, the necessary condition for the match formation is that the joint surplus $S_{i,j}$ is nonnegative:

$$W_{i,j} - U_i + J_{i,j} - V_j + H_j >= 0. \tag{2.3}$$

Let r denote the rate at which agents discount future. The discount rate r is given exogenously. The present discounted value of the expected income stream of an unemployed low-skilled worker U_l satisfies the following Bellman equation:

$$rU_l = b + \eta\theta q(\theta)(W_{s,l} - U_l). \tag{2.4}$$

In a perfect capital market the instantaneous return on the asset of being low-skilled unemployed rU_l is made of the flow unemployment income b and the expected capital gain from becoming employed $\eta\theta q(\theta)(W_{s,l} - U_l)$.

The present discounted value of the expected income stream of an unemployed high-skilled worker U_h satisfies the following Bellman equation:

$$rU_h = b + \eta\theta q(\theta)(W_{s,h} - U_h) + (1-\eta)\theta q(\theta)(W_{c,h} - U_h). \tag{2.5}$$

The instantaneous return on the asset of being high-skilled unemployed rU_h is made of the flow unemployment income b and the expected capital gain from becoming employed. With instantaneous probability $\eta\theta q(\theta)$ an unemployed high-skilled worker meets a simple vacancy and experiences the capital gain of $W_{s,h} - U_h$. With instantaneous probability $(1-\eta)\theta q(\theta)$ an unemployed high-skilled worker meets a complex vacancy and experiences the capital gain of $W_{c,h} - U_h$.

The present discounted value of the expected income stream of an employed worker of type j on a job of type i satisfies the following Bellman equation:

$$rW_{i,j} = w_{i,j} - \delta_i(W_{i,j} - U_j) \tag{2.6}$$

when $i = s$ and $j = l$ or $i = c$ and $j = h$. The instantaneous return on the asset of being a worker of type j employed on a job of type i $rW_{i,j}$ is made of the flow wage $w_{i,j}$ and the expected capital loss from becoming unemployed $-\delta_i(W_{i,j} - U_j)$ when $i = s$ and $j = l$ or $i = c$ and $j = h$.

The discounted present value of the expected income stream of a high-skilled worker employed on a simple job satisfies the following Bellman equation:

$$rW_{s,h} = w_{s,h} + (1-\eta)\theta q(\theta)(W_{c,h} - W_{s,h}) - \delta_s(W_{s,h} - U_h). \tag{2.7}$$

The instantaneous return on the asset of being a high-skilled worker employed on a new simple job $rW_{s,h}$ is made of the flow wage $w_{s,h}$ and the expected capital gain from changing state. With instantaneous probability $(1-\eta)\theta q(\theta)$ a high-skilled worker employed on a simple job finds a complex vacancy and experiences a capital gain of $W_{c,h} - W_{s,h}$, and with probability δ_s the match is destroyed, after which a worker becomes unemployed and experiences a capital loss of $W_{s,h} - U_h$.

The present discounted value of the expected stream of profits from a simple vacancy can be expressed:

$$rV_s = -\kappa + \psi q(\theta)(\phi(J_{s,l} - V_s + H_l) + (1-\phi)(J_{s,h} - V_s + H_h)).$$

The return on the asset of a simple vacancy rV_s consists of the flow cost of maintaining the vacancy -κ and of the expected capital gain from filling a vacancy. With instantaneous probability $\psi q(\theta)\phi$ a simple vacancy meets an unemployed low-skilled worker and experiences the capital gain of $J_{s,l} - V_s$. With instantaneous probability $\psi q(\theta)(1-\phi)$ a simple vacancy meets a high-skilled unemployed worker and experiences the capital gain of $J_{s,h} - V_s$.

The present discounted value of the expected stream of profits from a complex vacancy can be expressed:

$$rV_c = -\kappa + q(\theta)(1 - \psi\phi)(J_{c,h} - V_c + H_h).$$

The return on the asset of opening a complex vacancy rV_c is made of the flow cost of maintaining the vacancy κ and of the expected capital gain from the change of state $(1 - \psi\phi)(J_{c,h} - V_c + H_h)$.

The present discounted value of the expected stream of profits from a job of type i filled with a worker of type j can be expressed:

$$rJ_{i,j} = y_{i,j} + a_j - w_{i,j} - \delta_i(J_{i,j} - V_s + F_j) \tag{2.8}$$

when $i = s$ and $j = l$ or $i = c$ and $j = h$. The return on the asset of a new job of type i filled with a worker of type j $rJ_{i,j}$ is made of the flow profit $y_{i,j} + a_j - w_{i,j}$ and of the expected capital loss from job destruction $-\delta_i(J_{i,j} - V_i + F_j)$ when $i = s$ and $j = l$ or $i = c$ and $j = h$. The firm receives the employment subsidy a_l for every period it employs a worker of type j. The firm pays a one-time firing tax F_j once the match with a worker of type j is destroyed.

The present discounted value of the expected stream of profits from a simple job filled with a high-skilled worker can be expressed:

$$\begin{aligned} rJ_{s,h} &= y_{s,h} + a_h - w_{s,h} - \delta_s(J_{s,h} - V_s + F_h) \\ &- (1-\eta)\theta q(\theta)(J_{s,h} - V_s). \end{aligned} \tag{2.9}$$

The return on the asset of a simple job filled with a high-skilled worker $rJ_{s,h}$ is made of the flow profit $y_{s,h}+a_h-w_{s,h}$ and of the expected capital loss from the match break-up $-\delta_s(J_{s,h} - V_s + F_h) + (1-\eta)\theta q(\theta)(J_{s,h} - V_s)$. The matches between simple jobs and high-skilled workers terminate due to two reasons: exogenous jobs destruction which occurs at rate δ_s after which the firing tax F_h is imposed on a firm, and quit of high-skilled workers into complex jobs which occurs at rate $(1-\eta)\theta q(\theta)$. The firm does not pay the firing tax when the match terminates due to voluntary quit of a worker. The firm receives the employment subsidy a_h for every period it employs a high-skilled worker.

2.4 Cross-skill Matching Equilibrium

2.4.1 Definition of the Cross-Skill Matching Equilibrium

The cross-skill matching equilibrium is a vector $\{\theta, \eta, \phi, \psi, u\}$ that satisfies the following conditions:

1. Free entry: the present discounted values of the expected profits from unfilled jobs of both types V_s and V_c are equal to zero.

2. Individual rationality: At every instant, a firm of type i, $i = s, c$, and a worker of type j, $j = l, h$ stay in a match if and only if the total gain from the match

exceeds the gain that a worker and a firm can receive from leaving the match to search for another partner, *i.e.* if and only if the the surpluses associated with the three types of matches arising in the cross-skill matching equilibrium are all positive:

$$S_{s,l} > 0,\ S_{s,h} > 0,\ S_{c,h} > 0.$$

3. Steady-state flow conditions: the state variables the proportion of workers who are low skilled and employed $e_{s,l} = \mu - \phi u$, the proportion of workers who are high-skilled and employed on simple jobs $e_{s,h}$ and the proportion of workers who are high-skilled and employed on complex jobs $e_{c,h} = 1 - \mu - (1-\phi)u - e_{s,h}$ satisfy the steady state conditions under which the inflow of workers into each on these states is equal to the outflow. These steady-state conditions can be summarized as follows:

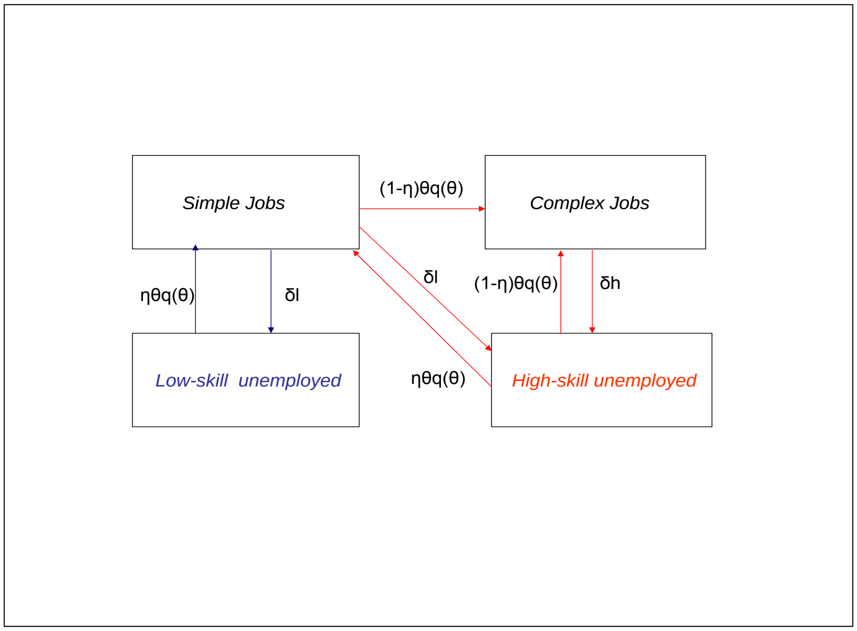
$$\eta\theta q(\theta)\phi u = \delta_s(\mu - \phi u) \tag{2.10}$$

$$\eta\theta q(\theta)(1-\phi)u = e(s,h)(\delta_s + \theta q(\theta)(1-\eta)) \tag{2.11}$$

$$(1-\eta)\theta q(\theta)((1-\phi)u + esh) = \delta_c(1 - \mu - (1-\phi)u - e(s,h)). \tag{2.12}$$

Equation (2.10) equates the inflow of low-skilled workers into employment $\eta\theta q(\theta)\phi u$ with the outflow of low-skilled workers from employment $\delta_s(1-\phi u)$. Equation (2.11) equates the inflow of high-skilled workers into employment in simple jobs $\eta\theta q(\theta)(1-\phi)u$ with the outflow of high-skilled workers from simple jobs $e(s,h)(\delta_s+\theta q(\theta)(1-\eta))$. Equation (2.12) equates the inflow of high-skilled workers into employment in complex jobs $(1-\eta)\theta q(\theta)((1-\phi)u + e(s,h))$ with the

Figure 2.1: Worker Flows



outflow of high-skilled workers from complex jobs, $(\delta_c(1-\mu-(1-\phi)u-e(s,h))$. Figure 2.1 summarizes worker flows in the equilibrium of the model.

2.4.2 Wages

This section derives the expressions for the equilibrium wages paid to workers of different skill types on jobs of different complexity types. After imposing the free-entry condition for simple and complex vacancies $V_s = 0$ and $V_c = 0$ the expected present discounted income of a worker of type j employed on a job of type i $W_{i,j}$ and the expected present discounted profit from a job of type i filled with a worker of type j $J_{i,j}$ for $i = s$ and $j = l$ or $i = c$ and $j = h$ become:

$$W_{i,j} = \frac{w_{i,j} + \delta_i U_j}{r + \delta_i}, \tag{2.13}$$

$$J_{i,j} = \frac{y_{i,j} + a_j - w_{i,j} - \delta_i F_j}{r + \delta_i}. \tag{2.14}$$

After substitution of equations (2.13) and (2.14) into the surplus sharing rule (2.2) the equilibrium wage of a worker of type j employed on a job of type i $w_{i,j}$ for $i = s$ and $j = l$ or $i = c$ and $j = h$ can be expressed:

$$w_{i,j} = rU_j + \beta(y_{i,j} + a_j + rH_j - \delta_i(F_j - H_j) - rU_j). \tag{2.15}$$

To derive the wage of a high-skilled worker on a simple job $w_{s,h}$ I first substitute equation (2.13) for $i = c$ and $j = h$ into equation (2.7) to obtain another expression for the expected present discounted value of a high-skilled worker on a simple job $W_{s,h}$:

$$W_{s,h} = \frac{(r + \delta_c)w_{s,h} + (1-\eta)\theta q(\theta) w_{c,h}}{(r + \delta_c)(r + \delta_s + (1-\eta)\theta q(\theta))} + \frac{U_h(\delta_s(r + \delta_c) + (1-\eta)\theta q(\theta)\delta_c)}{(r + \delta_c)(r + \delta_s + (1-\eta)\theta q(\theta))}. \tag{2.16}$$

After the free-entry condition for simple vacancies $V_s = 0$ is imposed, equation (2.9) can be solved for the expected present discounted stream of profits from a simple job filled with a high-skilled worker $J_{s,h}$:

$$J_{s,h} = \frac{y_{s,h} + a_h - w_{s,h} - \delta_s F_h}{r + \delta_s + (1-\eta)\theta q(\theta)}. \tag{2.17}$$

Finally, after the equations (2.16), (2.17) and (2.15) for $i = c$ and $j = h$ are substituted into the surplus sharing rule (2.2) and the free-entry condition for simple vacancies $V_s = 0$ is imposed, the wage of a high-skilled worker on a simple job $w_{s,h}$ can be expressed:

$$w_{s,h} = rU_h + \beta(y^*_{s,h} - rU_h) - (1-\beta)\theta q(\theta)(1-\eta)\beta \left[\frac{y^*_{c,h} - rU_h}{r+\delta_c}\right] \tag{2.18}$$

where $y^*_{s,h} = y_{s,h} + a_h - \delta_s F_h + (r + \delta_s + (1-\eta)\theta q(\theta))H_h$ and $y^*_{c,h} = y_{c,h} + a_h + rH_h - \delta_c(F_h - H_h)$. A high-skilled worker on a simple job earns less than the rU_h plus the share β of the flow surplus $y^*_{s,h} - rU_h$. The wage $w_{s,h}$ is reduced by the share $(1-\beta)$ of the worker's expected capital gain from on-the-job search.

Now the expressions for the equilibrium present discounted stream of incomes of unemployed low- and high-skilled workers U_l and U_h can be obtained. The expression for the present discounted stream of income of an unemployed low-skilled worker U_l can be obtained by substitution of equations (2.13) and (2.15) for $i = s$ and $j = l$ into equation (2.4):

$$rU_l = \frac{(r+\delta_s)b + \theta q(\theta)\eta\beta y^*_{s,l}}{(r+\delta_s) + \theta q(\theta)\eta\beta}, \tag{2.19}$$

where $y^*_{s,l} = y_{s,l} + a_l + rH_l - \delta_s(F_l - H_l)$. The expression for the expected present discounted stream of income of an unemployed high-skilled worker U_h can be obtained by substitution of equations (2.16), (2.18), and (2.13) and (2.15) for $i = c$ and $j = h$ into equation (2.5):

$$rU_h = \frac{(r+\delta_c)\lambda_3 b + \theta q(\theta)\beta[\eta(r+\delta_c)y^*_{s,h} + (1-\eta)\lambda_2 y^*_{c,h}]}{\lambda_1\lambda_2}, \tag{2.20}$$

where $y^*_{s,h} = y_{s,h} + a_h - \delta_s F_h + (r + \delta_s + (1-\eta)\theta q(\theta))H_h$, $y^*_{c,h} = y_{c,h} + a_h + rH_h - \delta_c(F_h - H_h)$, $\lambda_1 = r + \delta_c + \theta q(\theta)(1-\eta)\beta$, $\lambda_2 = r + \delta_s + \theta q(\theta)(1 - \eta + \eta\beta)$ and $\lambda_3 = r + \delta_s + \theta q(\theta)(1-\eta)$.

2.4.3 Match Surpluses

This section derives the expressions for the equilibrium surpluses from the matches between workers of different skill types and jobs of different complexity types. The expression for the surplus from the match between a worker of type j and a job of type i $S_{i,j}$ for $j = l$ and $i = s$ or $j = h$ and $i = c$ can be obtained by substituting equations (2.13) and (2.14) into equation (2.3) and imposing the free-entry conditions for vacancies $V_i = 0$:

$$S_{i,j} = \frac{y^*_{i,j} - rU_j}{r + \delta_i}, \tag{2.21}$$

where $y^*_{i,j} = y_{i,j} + a_j + rH_j - \delta_i(F_j - H_j)$.

Similarly, the expression for the surplus from a match between a high-skilled worker and a simple job $S_{s,h}$ can be obtained by substituting equations (2.16), (2.17) and (2.15) for $i = c$ and $j = h$ into equation (2.3) and imposing the free-entry condition for simple vacancies $V_s = 0$:

$$(r + \delta_s + \theta q(\theta)(1 - \eta))S_{s,h} = y^*_{s,h} - rU_h + \theta q(\theta)(1 - \eta)\beta \left(\frac{y^*_{c,h} - rU_h}{r + \delta_c} \right), \tag{2.22}$$

where $y^*_{s,h} = y_{s,h} + a_h - \delta_s F_h + (r + \delta_s + (1 - \eta)\theta q(\theta))H_h$.

Finally, after substitution of the expressions for the discounted present streams of income of unemployed low- and high-skilled workers U_l and U_h given in equations (2.19) and (2.20) into the equations (2.21) and (2.22) the expressions for the match surpluses $S_{s,l}$, $S_{s,h}$ and $S_{c,h}$ can be written as follows:

$$S_{s,l} = \frac{y^*_{s,l} - b}{r + \delta_s + \theta q(\theta)\eta\beta}, \tag{2.23}$$

$$S_{s,h} = \frac{y^*_{s,h} - b}{r + \delta_s + \theta q(\theta)(1 - \eta + \eta\beta)}, \tag{2.24}$$

$$S_{c,h} = \frac{[y^*_{c,h} - y^*_{s,h}]\theta q(\theta)\beta\eta + [y^*_{c,h} - b](r + \delta_s + \theta q(\theta)(1-\eta))}{\lambda_1\lambda_2}, \tag{2.25}$$

where for $i = s$ and $j = l$ or $i = c$ and $j = h$ $y^*_{i,j} = y_{i,j} + a_j + rH_j - \delta_i(F_j - H_j)$, $y^*_{s,h} = y_{s,h} + a_h - \delta_s F_h + (r + \delta_s + (1-\eta)\theta q(\theta))H_h$, $\lambda_1 = r + \delta_c + \theta q(\theta)(1-\eta)\beta$, $\lambda_2 = r + \delta_s + \theta q(\theta)(1 - \eta + \eta\beta)$ and $\lambda_3 = r + \delta_s + \theta q(\theta)(1-\eta)$.

It is easy to see that given the assumptions on the production technology the surplus from the match of a low-skilled worker and a simple job $S_{s,l}$, the surplus from the match of a high-skilled worker and a simple job $S_{s,h}$ and the surplus from the match of a high-skilled worker and a complex job $S_{c,h}$ are positive in the absence of policy measures, i.e. when a_j, H_j and F_j are all equal to zero. Therefore, in a policy-free economy it is always worthwhile for workers and firms to engage in the three types of matches possible in the cross-skill matching equilibrium. However, too high employment/firing taxes can make some of these surpluses negative, thus making it not worthwhile for firms and workers to engage in these types of matches. For example, a policy instrument a_h is interpreted as a lump-sum tax applied to matches which employ high-skilled workers if a_h is negative. In this case $S_{s,h}$ and $S_{c,h}$ can become negative if the absolute value of a_h is too high. Thus, introduction of some policies in a policy-free economy can potentially trigger a switch from the cross-skill matching equilibrium to an equilibrium in which a particular type of a match is not created, with important implications for labor market outcomes of workers of the two skill groups. In Chapter 3, where the joint posterior distribution of structural parameters of this model conditional on the relevant data in NLSY79 is obtained, it is assumed that the data has been generated by the policy-free cross-skill matching equilibrium. In Chapter 4, where the policy analysis is performed, only the policies that do not produce a switch away from the cross-skill matching equilibrium are considered, i.e. the analysis is limited to the policies that leave the surpluses in (2.23), (2.24) and (2.25) positive.

2.4.4 Free-entry Conditions

From the equations (2.3) and (2.2) the following relationship between the total surplus from the match between a job of type $i \in \{s, c\}$ and a worker of type $j \in \{l, h\}$ $S_{i,j}$ and a firm's surplus from the same match $(J_{i,j} - V_i + H_j)$ can be obtained:

$$(1 - \beta)S_{i,j} = (J_{i,j} - V_i + H_j).$$

Using this relationship the free-entry conditions for simple jobs $V_s = 0$ and for complex jobs $V_c = 0$ can be written as follows:

$$rV_s = -\kappa + \psi q(\theta)(1 - \beta)(\phi S_{s,l} + (1 - \phi)S_{s,h}) = 0, \tag{2.26}$$

$$rV_c = -\kappa + q(\theta)(1 - \psi\phi)(1 - \beta)S_{c,h} = 0. \tag{2.27}$$

Substituting the closed-form solutions for $S_{s,l}$, $S_{s,h}$ and $S_{c,h}$ given in equations (2.23)-(2.25) into (2.26) and (2.27) the free-entry conditions $V_s = 0$ and $V_c = 0$ become:

$$\frac{\kappa}{\psi q(\theta)} = (1 - \beta)\left(\phi\frac{y^*_{s,l} - b}{r + \delta_s + \theta q(\theta)\eta\beta} + (1 - \phi)\frac{y^*_{s,h} - b}{\lambda_2}\right), \tag{2.28}$$

$$\frac{\kappa}{(1-\psi\phi)q(\theta)} = (1-\beta)\left(\frac{y^*_{c,h}-b}{\lambda_1} - \theta q(\theta)\eta\beta\frac{y^*_{s,h}-b}{\lambda_1\lambda_2}\right), \tag{2.29}$$

where for $i = s$ and $j = l$ or $i = c$ and $j = h$ $y^*_{i,j} = y_{i,j} + a_j + rH_j - \delta_i(F_j - H_j)$, $y^*_{s,h} = y_{s,h} + a_h - \delta_s F_h + (r + \delta_s + (1-\eta)\theta q(\theta))H_h$, $\lambda_1 = r + \delta_c + \theta q(\theta)(1-\eta)\beta$, $\lambda_2 = r + \delta_s + \theta q(\theta)(1-\eta+\eta\beta)$ and $\lambda_3 = r + \delta_s + \theta q(\theta)(1-\eta)$. The left-hand sides of equations (2.28) and (2.29) represent the average costs of vacant simple and complex jobs respectively. At every instant a simple vacancy costs κ and is filled at the rate $\psi q(\theta)$, so the average cost of a simple vacancy is $\kappa/\psi q(\theta)$. Similarly, at every instant a complex vacancy costs κ and is filled at the rate $(1-\psi\phi)q(\theta)$, so the average cost of a complex vacancy is $\kappa/(1-\psi\phi)q(\theta)$. The right-hand sides of equations (2.28) and (2.29) represent the expected profits of filled simple and complex jobs respectively. Keeping constant θ, ϕ, ψ and η the expected profits from a filled simple job increase with employment and hiring subsidies a_l, a_h, H_l and H_h, and decrease as firing taxes F_l and F_h increase. Keeping constant θ, ϕ, ψ and η the expected profits from a filled complex job increase with employment subsidy a_h. The effect of increase in H_h is ambiguous: keeping θ, ϕ, ψ and η constant the expected profits from a filled complex job increase in H_h as long as $(r+\delta_c)(r+\delta_s+\theta q(\theta)(1-\eta+\eta\beta)) > \theta q(\theta)\eta\beta(r+\delta_s+(1-\eta)\theta q(\theta))$. Similarly, the effect of increase in F_h is ambiguous: keeping θ, ϕ, ψ and η constant the expected profits from a filled complex job decrease in F_h as long as $\delta_c(r+\delta_s+\theta q(\theta)(1-\eta+\eta\beta)) > \delta_s\theta q(\theta)\eta\beta$. Equations (2.28) and (2.29) state that in the steady-state equilibrium the expected cost of unfilled vacancies are equal to expected profits from filled jobs.

The two free-entry conditions (2.28) and (2.29) together with flow equations (2.10), (2.11), (2.12) determine the cross-skill matching equilibrium of the model defined by the vector of five endogenous variables θ, u, η, ψ, ϕ.

2.4.5 Possibility of a Corner Solution

Albrecht and Vroman (2002) and Dolado, Jansen, and Jimeno (2003) point out that when the proportion of low-skilled workers in the labor force μ is sufficiently high and/or the output of a complex job $y_{c,h}$ is sufficiently small, the cross-skill matching equilibrium will be a corner solution, *i.e.* only simple vacancies will be offered in the equilibrium. They also state the necessary condition which can be used to rule out the corner solution in the cross-skill matching equilibrium. In particular, this condition requires that when no complex vacancies are created, the expected stream of income to unfilled complex vacancy is positive; that is, $V_c > 0$ when $\eta = 1$. In the model in this chapter this condition can be stated as follows. When $\eta = 1$, the present discounted stream of income to unemployed low-skilled worker satisfies:

$$rU_l = \frac{b(r+\delta_s) + \theta q(\theta)\beta y^*_{s,l}}{r+\delta_s+\beta\theta q(\theta)}, \tag{2.30}$$

where $y^*_{s,l} = y_{s,l} + a_l + (r+\delta_s)H_l - \delta_s F_l$. Similarly, when $\eta = 1$, the present discounted stream of income to unemployed high-skilled worker satisfies:

$$rU_h = \frac{b(r+\delta_s) + \theta q(\theta)\beta y^o_{s,h}}{r+\delta_s+\beta\theta q(\theta)}, \tag{2.31}$$

where $y^o_{s,h} = y_{s,h} + a_h + (r+\delta_s)H_h - \delta_s F_h$. Substituting these expressions into the corresponding surplus expressions $S_{s,l}$ and $S_{s,h}$ given in equations (2.23) and (2.24) I obtain the surplus expressions for the case when no complex jobs are created:

$$S_{s,l} = \frac{y^*_{s,l} - b}{r + \delta_s + \theta q(\theta)\beta},$$
$$S_{s,h} = \frac{y^o_{s,h} - b}{r + \delta_s + \theta q(\theta)\beta}.$$

Next, these expressions are substituted into the free-entry condition $V_s = 0$ when no complex jobs are available to obtain:

$$\frac{\kappa}{q(\theta)} = (1-\beta)\frac{\mu y^*_{s,l} + (1-\mu)y^o_{s,h} - b}{r + \delta_s + \theta q(\theta)\beta}. \tag{2.32}$$

This equation has a unique solution for θ. Denote this solution θ^*. Then the necessary condition to ensure that firms are willing to open complex vacancies when $\eta = 1$ can be rewritten as $V_c > V_s = 0$. The surplus from a complex job when $\eta = 1$ can be written:

$$S_{c,h} = \frac{(y^*_{c,h} - b)(r + \delta_s) + (y^*_{c,h} - y^o_{s,h})\theta^* q(\theta^*)\beta}{(r + \delta_c)(r + \delta_s + \theta^* q(\theta^*)\beta)}. \tag{2.33}$$

This expression allows to write the necessary condition $V_c > V_s = 0$ as follows:

$$(1-\mu)\frac{(y^*_{c,h} - b)(r + \delta_s) + (y^*_{c,h} - y^o_{s,h})\theta^* q(\theta^*)\beta}{(r + \delta_c)(r + \delta_s + \theta^* q(\theta^*)\beta)} > \frac{\mu y^*_{s,l} + (1-\mu)y^o_{s,h} - b}{r + \delta_s + \theta^* q(\theta^*)\beta}. \tag{2.34}$$

This expression can be rewritten:

$$y^*_{c,h} - b > \frac{\mu(y^*_{s,l} - b)(r + \delta_c)}{(1-\mu)(r + \delta_s + \theta^* q(\theta^*)\beta)} + \frac{(y^o_{s,h} - b)(r + \delta_c + \theta^* q(\theta^*)\beta)}{r + \delta_s + \theta^* q(\theta^*)\beta}. \tag{2.35}$$

Thus, in order for firms to be willing to create complex vacancies the flow revenue from complex jobs must be higher than a certain linear combination of flow returs from a simple job filled with a low-skilled worker and that of a simple jobs filled with a high-skilled worker. The required differential increases with μ and δ_c and decreases with δ_s.

2.4.6 Wage Distribution in a Policy-Free Equilibrium

This section compares wages paid to workers on simple and complex jobs in a policy-free economy. The results of this comparison will be used in chapter 3 to construct the prior distribution of parameters.

The difference between the wages of high-skilled workers on simple jobs and those of low-skilled workers on complex jobs in the policy-free cross-skill matching equilibrium can be expressed:

$$\begin{aligned} w_{s,h} - w_{s,l} &= rU_h + \beta(y_{s,h} - rU_h) - (1-\beta)\theta q(\theta)(1-\eta)\beta\frac{y_{c,h} - rU_h}{r + \delta_c} \\ &- rU_l - \beta(y_{s,l} - rU_l). \end{aligned} \tag{2.36}$$

The expression $rU_h - rU_l$ can be written:

$$rU_h - rU_l = \theta q(\theta)\beta[\eta(S_{s,h} - S_{s,l}) + (1-\eta)S_{c,h}]. \tag{2.37}$$

After substitution of this expression in (2.36), the following expression for the wage differential can be obtained:

$$w_{s,h} - w_{s,l} = (1-\beta)\theta q(\theta)\eta(S_{s,h} - S_{s,l}) + \beta(y_{s,h} - y_{s,l}). \tag{2.38}$$

By assumption on the production technology, $y_{s,h} - y_{s,l}$ is positive. However, the sign of $S_{s,h} - S_{s,l}$ depends on the relative productivity of high- and low-skilled workers on simple jobs. Therefore, the sign of the wage differential $w_{s,h} - w_{s,l}$ is ambiguous.

To compare wages of mismatched high-skilled workers and those of high-skilled workers on complex jobs the relevant wage differential in the policy-free equilibrium can be expressed:

$$\begin{aligned} w_{s,h} - w_{c,h} &= rU_h + \beta(y_{s,h} - rU_h) - (1-\beta)\theta q(\theta)(1-\eta)\beta S_{c,h} \\ &- rU_h - \beta(y_{c,h} - rU_h) \\ &= \beta(y_{s,h} - y_{c,h}) - (1-\beta)\theta q(\theta)(1-\eta)\beta S_{c,h}. \end{aligned} \tag{2.39}$$

It is easy to see, that this wage differential is negative, as $y_{c,h} > y_{s,h}$ by assumption, and $S_{c,h}$ is shown to be positive given the assumptions. Thus, the wage of a high-skilled worker on complex jobs is always higher than the wage of a mismatched high-skilled workers.

To compare wages of high-skilled workers on complex jobs and those of low-skilled workers on simple jobs the relevant wage differential in the policy-free equilibrium can be expressed:

$$w_{c,h} - w_{s,l} = (rU_h - rU_l)(1-\beta) + (y_{c,h} - y_{s,l})\beta.$$

It easy to see that this wage differential is positive as long as $rU_h > rU_l$. It is not obvious that this inequality would hold for any combination of parameter values. High-skilled workers have higher exit from unemployment than low-skilled workers and qualify for more productive complex jobs, which tends to increase their present discounted stream of income while unemployed relative to that of low-skilled workers. On the other hand, the productivity of high-skilled workers on simple jobs may be lower than that of low-skilled workers and the rate of job destruction of complex jobs may be higher than that of simple jobs, which would tend to decrease the present discounted stream of income of unemployed high-skilled workers relative to that of low-skilled workers. Net effect of these two forces on the value of unemployment of high-skilled workers is unclear. In my numerical simulations I found that $rU_h > rU_l$ as long as the necessary condition for firm entry into complex sector as stated in (2.35) is satisfied. Although skill distribution is exogenous in the model, it is natural to assume that individual's decision to acquire skill is motivated by the desire to take advantage of higher expected returns offered in the labor market to high-skilled workers. Therefore, in chapter 3 I assume that the structural parameters of the model are such that $rU_h > rU_l$, which would imply that the difference between the wage of a high-skilled worker on complex job and that of a low-skilled worker $w_{c,h} - w_{s,l}$ is positive in the policy-free equilibrium.

CHAPTER 3

DATA AND INFERENCE

The model in chapter 2 generates a steady-state joint distribution of unemployment durations, wages and employment durations for a population of individuals. This distribution depends on all structural parameters of the model: $y_{s,l}$, $y_{s,h}$, $y_{c,h}$, δ_s, δ_c, μ, β, κ, b, r as well as the function $m(.,.)$. To obtain the joint posterior distribution of structural parameters I utilize information on the duration of the first unemployment spell after the school leaving and the duration and wages of the first full-time jobs of the respondents to the National Longitudinal Survey of Youth 1979 cohort (NLSY79). This data source was chosen because skill mismatch is more likely to occur among workers with low labor market experience. For instance, Sicherman (1991) finds that overqualified workers tend to have less labor market experience than workers who are not overqualified. Following Mortensen and Pissarides (2003) who treat US economy as a policy-free environment, I assume that my data sample has been generated by the policy-free cross-skill matching equilibrium of the model.

In the identification of skill of a worker and complexity of a job I make use of the information on the Armed Forces Qualification Test (AFQT) scores of individuals which is available for all respondents to the NLSY79, as well as of the information on the intelligence requirement of the occupation (IRO) of the first full-time job as estimated by Ingram and Neumann (2006) from occupational characteristics contained in the Dictionary of Occupational Titles (DOT). Ingram and Neumann (2006) performed factor analysis on 54 characteristics of occupations contained in DOT to reduce them to a four-dimensional skill measure. One of the four factors, named subsequently the intelligence requirement of occupation, was found to be positively correlated with such occupational requirements as general intelligence, language development, verbal and numerical aptitude. Ingram and Neumann (2006) find that skilled occupations, such as scientists, lawyers, and physicians are associated with high levels of IRO, and occupations which involve repetitive work and low requirements of verbal and numerical ability are characterized by low levels of IRO. In my inference I associate IRO with job complexity by assuming that on average complex occupations have higher levels of IRO than simple occupations.

This chapter contains the detailed description of the data and the Bayesian procedure I develop to obtain the joint posterior distribution of the structural parameters of the model.

3.1 Data

NLSY79 was administered to 12686 individuals who were 14 to 21 years old as of January 1 1979. The first interview was conducted in 1979 and the subsequent interviews were conducted on an annual basis until 1994 and on a biannual basis starting from 1994. The survey consists of a nationally representative core sample, oversamples of blacks, hispanics and economically disadvantaged non-blacks/non-hispanics, and a military oversample. I use the data on white males in the core sample. There are four educational groups in my sample: high-school drop-outs, high-school graduates, individuals with some college, individuals with college degree or higher than college degree.

The NLSY79 work history files provide detailed weekly accounts of the labor market experience of the respondents beginning at January 1 1978. I use this information to construct the duration of unemployment after the school leaving and duration of the employment on the first occupation within the first full-time job. The observations on individuals who left school before January 1 1978 or returned to school after leaving it for the first time are omitted from my sample. I define the first full-time job as an occupation in which the respondent worked at least 35 hours per week for more than 12 weeks without changing employer. These restrictions ensure that the first job is not a temporary summer job and are consistent with the definition of the first full-time job used in Eckstein and Wolpin (1990), who used this dataset to estimate the equilibrium search model of Albrecht and Axell (1985). The duration of unemployed search is then defined as the number of weeks between school completion and the start of the first full-time job. The duration of the employment on the first full-time job is defined as a number of weeks between the start of the employment with the first full-time job and the week this employment ended by quit, lay-off or transition to another employer or occupation, or was interrupted by a non-employment spell or a spell with another employer or occupation which lasted more than 2 months. Because the respondents to the NLSY79 are observed until 2002 the censoring rate in the measurement of the duration of employment with the first occupations is nearly 0. The wage data used is the weekly real wage (in 1986 dollars) reported in the first week of employment.

There are 1152 individuals in the sample who comply with the following additional restrictions: the information about the week of school completion is not absent, an individual did not return back to school or obtained a GED after leaving school for the first time, the individual left high school after January 1st 1978. From these 1152 observations I delete 103 on individuals whose first full-time job was not in the private sector. I also delete 39 observations on individuals who did not have wage information for their first full-time job, 45 observations on individuals who did not have AFQT score information and 95 individuals who ever served in the military. Also, I do not use information on individuals whose non-employment after the school leaving lasted longer than 200 weeks, or the wage on the first full-time job was less than 55 dollars per week. This last restriction resulted in the deletion of 40 observations. There are 830 observations in the final sample: 96 high-school drop-outs (12% of observations) , 482 high-school completers (58% of observations), 90 individuals with some college (11% of observations) and 162 individuals with college degree or higher degree (19% of observations). Some individuals (199 respondents, which makes 24% of the sample) were already employed during the week they left school. The duration of employment for these individuals is computed as the difference between the week that the employment with the first full-time occupation ended and the week it began, which happened prior to the week of school leaving.

It is possible that the probability that an individual is already employed by the the week she leaves school is related to her skill level. In particular, one can expect that a high-skilled individual is more likely to be already employed by the final week of school than a low-skilled individual. I investigate whether this is true in my data by estimating the following probit regression:

$$Prob(I_i = 1|x_i) = \Phi(x_i\alpha)$$

where $I_i = 1$ if individual i is employed during the week she left school, and $I_i = 0$ otherwise. Vector x_i includes variables which are informative about the skill level of individual i: $x_i = [1, afqt_i, f1_i, lnw_i, EDU_i]$, where $afqt_i$ is the AFQT score of individual i, $f1_i$ is the intelligence requirement of her first occupation, lnw_i is the natural logarithm of her wage on the first job and EDU_i is her number of years of schooling. $\Phi(.)$ denotes the standard normal cdf. Table 3.1 contains the coefficients and standard errors from fitting this model to my data sample. From these results I conclude that contrary to the expectations the variables which are positively related to the skill level of individual i have no effect on her probability of being already employed by the week she left school, because none of the coefficients is statistically significant at 10% level. Therefore, in formulating the likelihood function of the observables I will assume that the information on the job search durations DU is missing completely at random for individuals who were already employed by the week they left school.

Table 3.2 presents the descriptive statistics of the sample partitioned into four groups by years of education. I use DU to denote the number of weeks between the week of school leaving and the week when the first full-time employment began. The duration of employment with the first full-time occupation is also measured in weeks

Table 3.1: Determinants of Being Employed During the Week of Leaving School

Variable	Coefficient	Standard Error
AFQT	-.029	0.065
IRO	-.031	0.063
ln w	-.181	0.125
EDU	.016	0.033
const	.047	0.734
Log L	-455.29	
Observations	830	

and is denoted by DJ. Wages are 1986$ weekly wages. I standardize the AFQT scores within my sample, so that the sample mean of AFQT scores is approximately 0 and the sample standard deviation is approximately 1. IRO is normalized by Ingram and Neumann (2006) to have mean of 0 and a standard deviation of approximately 1 in the CPS wave of 1971.

The sample histograms of the durations, wages, AFQT scores and IRO for different educational groups are presented in Figures 3.1-3.5. The model predicts that the duration of unemployment of low-skilled workers should be longer than that of high-skilled workers. Also, the model predicts that there is some skill mismatch on the first job and that the expected duration of a match between a high-skilled worker and a simple job is shorter than that of a low-skilled worker and a simple job. The data is consistent with basic predictions of the model: the duration of unemployment decreases with skill level of a worker measured by either AFQT score or years of education. There is some skill mismatch: about 20% of the respondents with at least 16 years of education are employed in occupations with the intelligence requirement

Table 3.2: Sample Moments

Variable	Mean	Std. Dev	Min	Max
edu<12; 96 obs.				
DU, weeks	54.47	50.57	1	198
DJ, weeks	41.9	53.4	13	406
wage, 1986$ per week	198.4	84.7	57.3	559.6
afqt, standardized	-1.06	.67	-2.52	.71
IRO	-.87	.61	-1.66	1.56
edu=12; 482 obs.				
DU, weeks	42.08	45.36	1	200
DJ, weeks	48.5	44.97	13	474
wage, 1986$ per week	215.5	109.9	55.8	1031.5
afqt, standardized	-.22	.81	-2.2	1.54
IRO	-.64	.71	-1.68	1.35
edu > 12 and < 16; 90 obs.				
DU, weeks	26.8	35.24	1	190
DJ, weeks	45.3	30.93	14	224
wage, 1986$ per week	233	107.5	66.7	742.7
afqt, standardized	.29	.78	-1.95	1.65
IRO	-.12	.87	-1.52	2.11
edu>=16; 162 obs.				
DU, weeks	22.02	24	1	140
DJ, weeks	66.03	74	13	479
wage, 1986$ per week	333.6	134.66	84.6	791.9
afqt, standardized	1.00	.52	-1.00	1.73
IRO	.81	.89	-1.66	2.17

of occupation (IRO) less than 0. The data is also consistent with on-the-job search by mismatched workers: the mean employment duration of the respondents with at least 16 years of education employed in occupations with the intelligence requirement of occupation (IRO) less than 0 is 37 weeks, while the mean employment duration of respondents with educational attainment of 12 years or less employed in occupations with IRO less than 0 is 47 weeks.

Figure 3.1: Histogram of Unemployment Durations

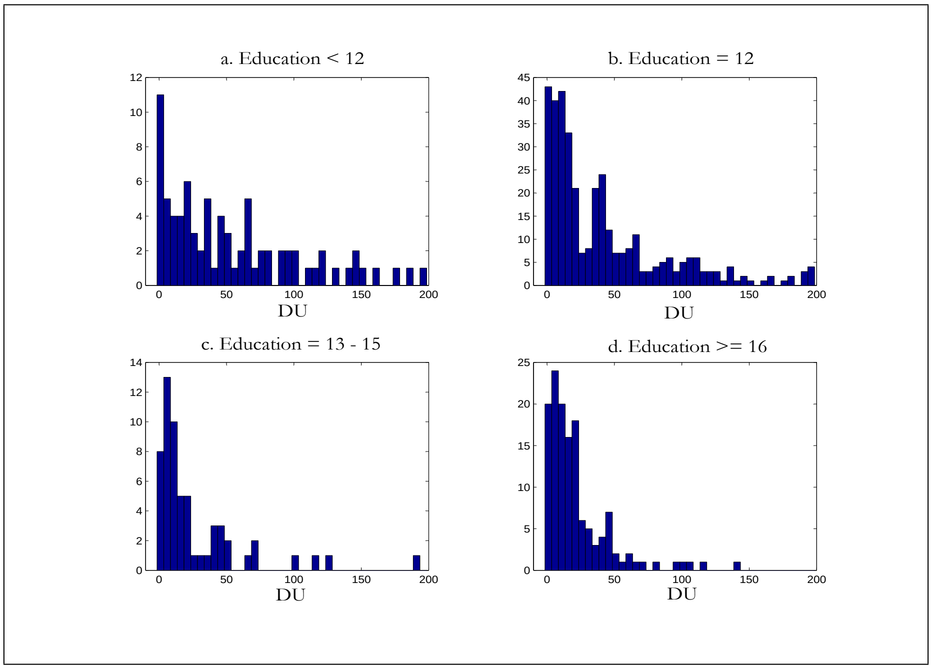


Figure 3.2: Histogram of Job Durations

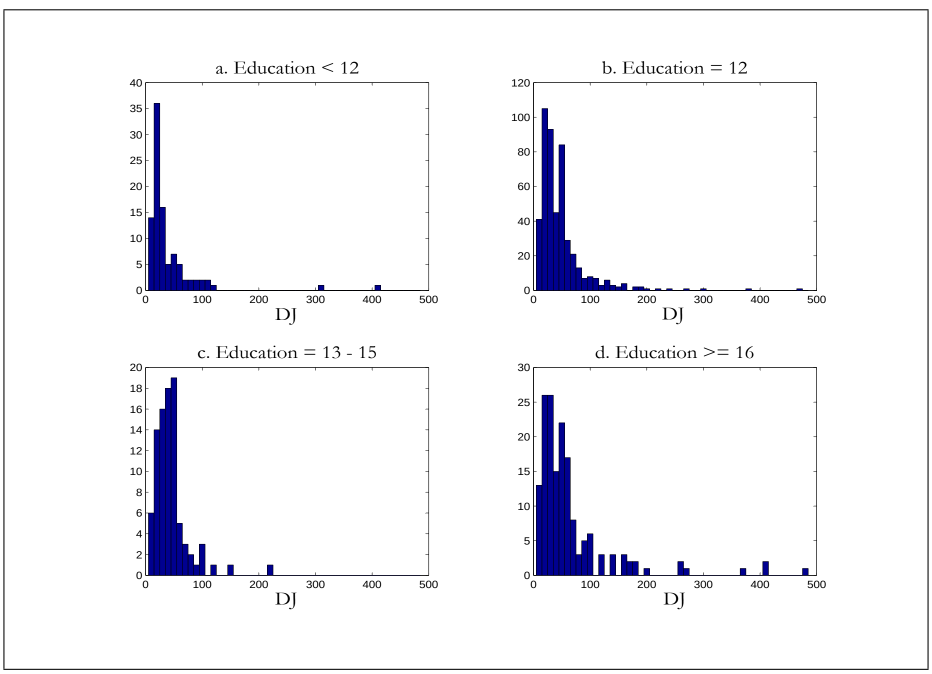


Figure 3.3: Histogram of Wages

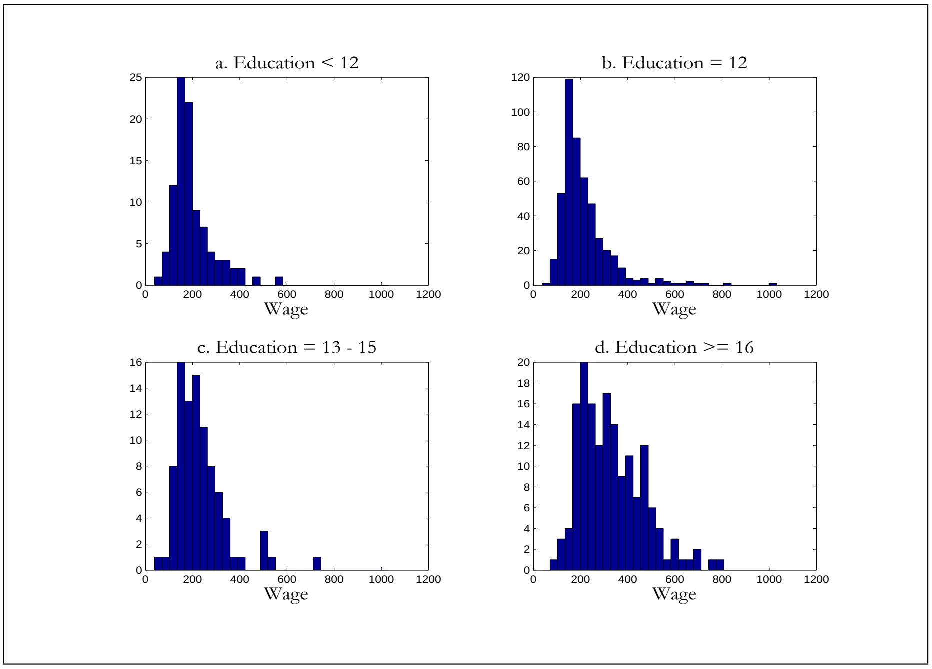


Figure 3.4: Histogram of AFQT scores

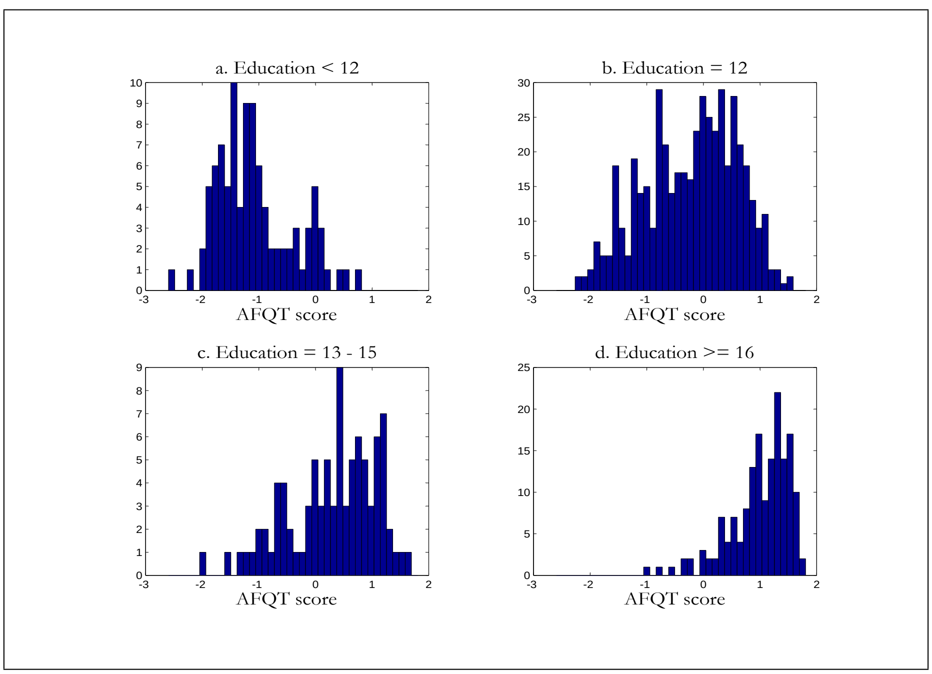
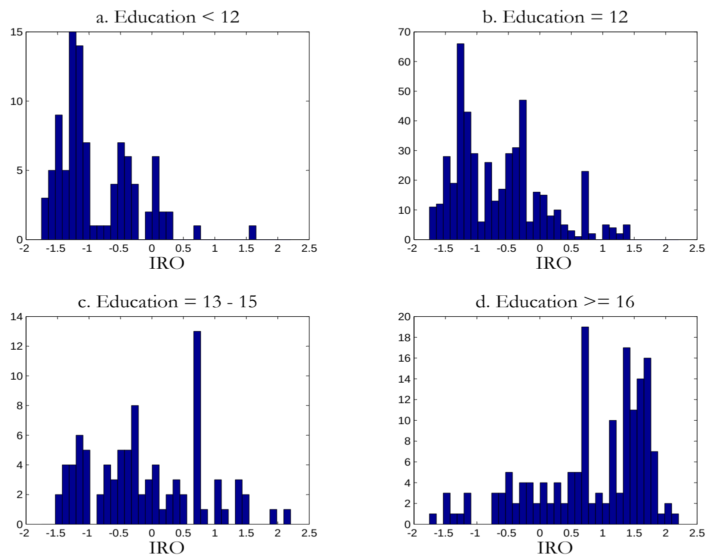


Figure 3.5: Histogram of IRO



3.2 The Probability Density of the Observables

In the identification of skill of a worker and complexity of a job I make use of the information on the AFQT scores of individuals and the intelligence requirement of the occupation (IRO) of the first full-time occupation. I associate workers' skill levels with AFQT scores of the respondents and jobs' complexity levels with the intelligence requirement of the first full-time occupation IRO. I assume that *on average* the AFQT scores of high-skilled individuals are higher than those of low-skilled individuals, and that *on average* complex occupations have higher IRO than simple occupations, but the skill level of a worker and the complexity of a job in the realized matches in the sample are not observed. By making this assumption I avoid division of workers and jobs into skill and job complexity groups based on necessarily somewhat arbitrary cut-off points in the range of variables selected to measure skill and complexity. The joint likelihood of unemployment and employment durations, wage, AFQT score, the intelligence requirement of occupation and the measure of educational attainment EDU for individual i is a mixture over three latent states corresponding to three types of skill-complexity matches between workers and firms arising in a cross-skill matching equilibrium of the model: low-skilled workers on simple jobs, high-skilled workers on simple jobs, high-skilled workers on complex jobs. The state-specific distributions of durations and wages are generated by the model, and I make additional assumptions about the state-specific distributions of AFQT scores, the intelligence requirement of occupations IRO and the measure of educational attainment EDU.

3.2.1 Latent Indicators of Mixture Components

Bayesian inference in mixture models is often facilitated by data augmentation, in which the portion of the data to be augmented is taken to be a latent indicator of mixture component for each observation. I follow the same strategy and introduce the latent state $k_i \in \{1, 2, 3\}$ for each individual i, so that $k_i = 1$ if individual i is low-skilled and her first job is simple, $k_i = 2$ if individual i is high-skilled and her first job is simple, and $k_i = 3$ if individual i is high-skilled and her first job is complex $i = 1, ..., N$, where N is a sample size. The model specifies the following unconditional probabilities of worker's being in each of the three latent states:

$$P[k_i = 1|\omega] = \mu \tag{3.1}$$

$$P[k_i = 2|\omega] = (1-\mu)\eta \tag{3.2}$$

$$P[k_i = 3|\omega] = (1-\mu)(1-\eta), \tag{3.3}$$

where ω is the vector of parameters. These probabilities are obtained under the following assumption about the data generating process: a small cohort of workers representative of the entire population of workers enters the labor market and draws from the equilibrium distribution of jobs. The proportion μ of workers in the cohort are low-skilled and their first job is necessarily simple, hence (3.1); the proportion $1-\mu$ of workers in the cohort are high-skilled and the fraction of simple vacancies in the mass of vacancies is η, therefore an unemployed high-skilled worker meets a simple job with probability η, and a complex job with probability $(1-\eta)$, hence (3.2) and (3.3).

Let $\mathbf{d}$ denote a matrix of the sample data on durations, wages, AFQT scores, the intelligence requirement of occupations on the first job and educational attainment, and d_i denote the vector of the data on durations, wages, AFQT scores, the intelligence requirement of occupations on the first job and educational attainment for individual i. The mixture specification implies that the $p(\mathbf{d}|\omega)$ is of the form

$$\begin{aligned} p(\mathbf{d}|\omega) = \prod_{i=1}^{N} [\mu p(d_i|\omega, k_i = 1) &+ (1-\mu)\eta p(d_i|\omega, k_i = 2) \\ &+ (1-\mu)(1-\eta) p(d_i|\omega, k_i = 3)]. \end{aligned} \tag{3.4}$$

Let $\mathbf{k} = [k_1, \ldots, k_N]'$ be a latent vector of state assignments for N individuals of the sample. Then

$$P(\mathbf{d}|\omega, \mathbf{k}) = \prod_{i=1}^{N} P(d_i|\omega, k_i = j), i = 1, ..., N, j = 1, 2, 3. \tag{3.5}$$

Define

$$\begin{aligned} n_l &= \sum_{i=1}^{N} \Delta(k_i, 1), \\ n_{sh} &= \sum_{i=1}^{N} \Delta(k_i, 2), \\ n_{ch} &= \sum_{i=1}^{N} \Delta(k_i, 3), \end{aligned} \tag{3.6}$$

where n_l denotes the number individuals with $k_i = 1$, n_{sh} denotes the number of individuals with $k_i = 2$, n_{ch} denotes the number of individuals with $k_i = 3$ and $\Delta(a, b)$ is the Kroneker delta function defined as $\Delta(a, b) = 1$ if $a = b$, and $\Delta(a, b) = 0$ if $a \neq b$. Note, that n_l, n_{sh} and n_{ch} are latent random variables. Then

$$p(\mathbf{k}|\omega) = \prod_{i=1}^{N} P(k_i|\omega) = \mu^{n_l}[(1-\mu)\eta]^{n_{sh}}[(1-\mu)(1-\eta)]^{n_{ch}}, \tag{3.7}$$

and the conditional on the parameters joint density of data and the state assignment $\mathbf{k}$ is the product of (3.5) and (3.7):

$$\begin{aligned} p(\mathbf{d}, \mathbf{k}|\omega) &= \prod_{i=1}^{N} P(d_i|\omega, k_i = j)\mu^{n_l}[(1-\mu)\eta]^{n_{sh}}[(1-\mu)(1-\eta)]^{n_{ch}} \\ i &= 1, ..., N, j = 1, 2, 3. \end{aligned} \tag{3.8}$$

3.2.2 Unemployment and Employment Durations

In the model the exit of unemployed low-skilled workers into employment is governed by a Poisson process with rate $\eta\theta q(\theta)$. Therefore, the distribution of unemployed job search durations DU_i of low-skilled workers is exponential with parameter

$\eta\theta q(\theta)$. The matches between low-skilled workers and simple jobs are destroyed in a Poisson process with rate δ_s, therefore the employment duration of low-skilled workers is exponentially distributed with parameter δ_l. Thus,

$$p(DU_i, DJ_i|\omega, k_i = 1) = \eta\theta q(\theta)\exp\{-\eta\theta q(\theta)DU_i\}\delta_l \exp\{-\delta_l DJ_i\}, \tag{3.9}$$

where ω is the vector of parameters.

Employment opportunities for high-skilled workers arrive in a Poisson process at rate $\theta q(\theta)$. Therefore, the unemployed job search duration of high-skilled workers is exponential with parameter $\theta q(\theta)$. High-skilled worker can be employed on simple and complex jobs. The dissolution of matches between high-skilled workers and simple jobs is governed by a Poisson process with the rate $(\delta_l + (1-\eta)\theta q(\theta))$. The expression $(1-\eta)\theta q(\theta)$ is the rate at which mismatched high-skilled workers find employment in complex jobs. Therefore, the duration of the first job of individual i conditional on job's being simple and on individual's being high-skilled, is distributed exponentially with parameter $(\delta_l + (1-\eta)\theta q(\theta))$. Thus,

$$\begin{aligned} p(DU_i, DJ_i|\omega, k_i = 2) &= \theta q(\theta)\exp\{-\theta q(\theta)DU_i\} \\ &\times (\delta_l + (1-\eta)\theta q(\theta))\exp\{-(\delta_l + (1-\eta)\theta q(\theta))DJ_i\}, \end{aligned} \tag{3.10}$$

where ω is the vector of parameters.

The dissolution of matched between high-skilled workers and complex jobs is governed by a Poisson process with rate δ_c. Therefore, the duration of the first job of individual i conditional on individual's being high-skilled and job's being complex is exponentially distributed with parameter δ_h. Thus,

$$p(DU_i, DJ_i|\omega, k_i = 3) = \theta q(\theta)\exp\{-\theta q(\theta)DU_i\}\delta_h \exp\{-\delta_h DJ_i\}, \tag{3.11}$$

where ω is the vector of parameters.

3.2.3 Wages, AFQT Score and IRO

The model generates a discrete wage distribution with three points in its support: $w_{s,l}$, $w_{s,h}$, $w_{c,h}$. However, the discrete distribution with three points in the support is not a characteristic of the observed wages, therefore further distributional assumptions are required to make use of the wage data. I follow Eckstein and Wolpin (1990) who estimate the Albrecht and Axell (1985) model which produces a discrete distribution of equilibrium wages, as the model in chapter 2, and assume that observed wages are measured with error coming from a continuous parametric distribution. In particular, I assume that conditional on the latent state the observed wage is lognormal:

$$lnw_i|(\omega, k_i = j) \sim N(w_j^*, (h_{w,j})^{-1}), \qquad i = 1, ..., N, j = 1, 2, 3, \tag{3.12}$$

where $w_1^* = ln(w_{s,l})$, $w_2^* = ln(w_{s,h})$, $w_3^* = ln(w_{c,h})$ and $h_{w,j}$ denotes the state-specific precision (the inverse of the variance) of the natural logarithm of observed wages for $j = 1, 2, 3$.

I use AFQT scores and the intelligence requirement of the occupation IRO in the identification of skill type of a worker and of complexity type of a job. I assume that:

$$afqt_i|(\omega, k_i = j) \sim N(x_l, (h_{afqt,l})^{-1}) \text{ for } j = 1$$

and

$$afqt_i|\omega, k_i = j \sim N(x_h, (h_{afqt,h})^{-1}) \text{ for } j = 2, 3,$$

where $x_l < x_h$.

Similarly,

$$f1_i|\omega, k_i = j \sim N(y_s, (h_{f1,s})^{-1}) \text{ for } j = 1, 2$$

and

$$f1_i|\omega, k_i = j \sim N(y_c, (h_{f1,c})^{-1}) \text{ for } j = 3,$$

where $y_s < y_c$. Thus, I assume that on average AFTQ scores of high-skilled individuals are higher than those of low-skilled individuals, and the intelligence requirement of the occupation on the complex jobs is higher than those on simple jobs.

The joint conditional distribution of lnw_i, $afqt_i$, $f1_i$ can be written compactly as follows. Let $\mathbf{w}^* = [w_1^*, w_2^*, w_3^*]'$ denote the vector of state-specific means of natural logarithm of observed wages, $\mathbf{x} = [x_l, x_h]'$ denote the vector of state-specific means of AFQT scores and $\mathbf{y} = (y_s, y_c)'$ denote the vector of state-specific means of IRO. Also, let $\mathbf{ln\ w} = [lnw_1, \ldots, lnw_N]'$, $\mathbf{afqt} = [afqt_1, \ldots, afqt_N]'$, $\mathbf{f1} = [f1_1, \ldots, f1_N]'$ denote the vectors of the sample data on log wages, AFQT score and IRO respectively. Also define

$$\underset{N\times 3}{\mathbf{z}(\mathbf{k})} = \mathbf{z} = [\mathbf{z}_1, \ldots, \mathbf{z}_N]' = [\Delta(k_i, j)],$$

where $\Delta(a, b)$ is the Kroneker delta function defined as $\Delta(a, b) = 1$ if $a = b$, and $\Delta(a, b) = 0$ if $a \neq b$. Thus, $z_{i,j} = 1$ if the state of individual i $k_i = j$ and $z_{i,j} = 0$

otherwise. Let

$$\underset{3N\times 7}{\mathbf{Z}} = \begin{pmatrix} \mathbf{z} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{z}\cdot\mathbf{o}_1 & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{z}\cdot\mathbf{o}_2 \end{pmatrix},$$

where $\mathbf{o}_1 = \begin{pmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 1 \end{pmatrix}$, and $\mathbf{o}_2 = \begin{pmatrix} 1 & 0 \\ 1 & 0 \\ 0 & 1 \end{pmatrix}$.

Also define

$$\underset{3N\times 1}{\mathbf{e}} = \begin{pmatrix} \mathbf{ln\ w} \\ \mathbf{afqt} \\ \mathbf{f1} \end{pmatrix}, \quad \underset{7\times 1}{\boldsymbol{\gamma}} = \begin{pmatrix} \mathbf{w}^* \\ \mathbf{x} \\ \mathbf{y} \end{pmatrix}$$

and

$$\begin{aligned} \underset{3N\times 3N}{\mathbf{Q}(\mathbf{k})} = \mathbf{Q} = \ & diag(h_{w,k_i}, ..., h_{w,k_N}, h_{afqt,k_i}, ..., h_{afqt,k_N}, \\ & h_{f1,k_i}, ..., h_{f1,k_N}), \end{aligned}$$

where $diag(\mathbf{a})$ denotes a diagonal matrix with vector of diagonal elements $\mathbf{a}$. Then the joint probability density of log wages, AFQT scores and IRO conditional on ω and $\mathbf{k}$ can be written:

$$p(\mathbf{e}|\omega, \mathbf{k}) = (2\pi)^{-3N/2}|\mathbf{Q}|^{1/2}\exp[-(\mathbf{e}-\mathbf{Z}\boldsymbol{\gamma})'\,\mathbf{Q}\,(\mathbf{e}-\mathbf{Z}\boldsymbol{\gamma})\,/2], \tag{3.13}$$

where ω is the vector of parameters.

3.2.4 Measure of Educational Attainment EDU

The measure of educational attainment EDU is defined as a variable which takes value 1 if individual has less than 12 years of education, takes value 2 if individual has 12 years of education, takes value 3 if individual has 13, 14 or 15 years of education, and takes value 4 if individual has 16 or more years of education. I specify the following conditional distribution of EDU_i: $p(EDU_i = E|k_i = j, \omega) = \pi_{E,l}$ for $j = 1$ and $p(EDU_i = E|k_i = j, \omega) = \pi_{E,h}$ for $j = 2, 3$, where $E = 1, ..., 4$, $i = 1, ..., N$, $\pi_{1,l} + \pi_{2,l} + \pi_{3,l} + \pi_{4,l} = 1$ and $\pi_{1,h} + \pi_{2,h} + \pi_{3,h} + \pi_{4,h} = 1$. Thus, conditional on the latent state assignment $\mathbf{k}$ the independent finite state model is specified for the random variable EDU. Let **EDU** denote the $N \times 1$ vector of a collection of observables EDU_i for N individuals in the sample. Define $m_{E,l} = \sum_{i=1}^{N} \Delta(EDU_i, E) \cdot \Delta(k_i, 1)$ where $\Delta(a, b)$ is the Kroneker delta function defined as $\Delta(a, b) = 1$ if $a = b$, and $\Delta(a, b) = 0$ if $a \neq b$. Thus, $m_{E,l}$ is the number of individuals with $EDU_i = E$ and the latent state $k_i = 1$. Also, define $m_{E,h} = \sum_{i=1}^{N} \Delta(EDU_i, E) \cdot (\Delta(k_i, 2) + \Delta(k_i, 3))$. Similarly, $m_{E,h}$ is the number of individuals with $EDU_i = E$ and the latent state $k_i = 2$ or $k_i = 3$. Then the conditional probability density function of **EDU** can be written:

$$p(\mathbf{EDU}|\omega, \mathbf{k}) = \prod_{E=1}^{4} \pi_{E,l}^{m_{E,l}} \cdot \pi_{E,h}^{m_{E,h}}, \tag{3.14}$$

where ω is the vector of parameters. The parameters $\pi_{E,l}$ and $\pi_{E,h}$ for $E = 1, ..., 4$ will be used in section 3.4 to obtain the posterior probability of individual's being skilled conditional on her educational attainment, which in turn will be used in chapter 4 to predict the impacts of the policies on labor market outcomes of workers with different educational attainment.

3.2.5 Joint Conditional Data Density

Define DUj and DJj for $j = 1, 2, 3$ as follows:

$$DUj = \sum_{i=1}^{N} (DU_i \Delta(k_i, j)),$$

$$DJj = \sum_{i=1}^{N} (DJ_i \Delta(k_i, j)).$$

Then the joint conditional on ω and $\mathbf{k}$ probability density of the observables unemployment duration DU_i, job duration DJ_i, natural log of wage lnw_i, AFQT score $afqt_i$, intelligence requirement of occupation $f1_i$ and measure of educational attainment EDU_i for individual i is a product of $p(DU_i, DJ_i|\omega, k_i = j)$, $p(lnw_i|\omega, k_i = j)$, $p(afqt_i|\omega, k_i = j)$, $p(f1_i|\omega, k_i = j)$ and $p(EDU_i|k_i = j, \omega)$. Therefore, the joint conditional probability density function of the observables $\{DU_i\}_{i=1}^N$, $\{DJ_i\}_{i=1}^N$, $\mathbf{e}$ and $\mathbf{EDU}$ can be written as follows:

$$\begin{aligned} & p\big(\{DU_i\}_{i=1}^N, \{DJ_i\}_{i=1}^N, \mathbf{e}|\omega, \mathbf{k}, \mathbf{EDU}\big) = \eta^{n_l} \theta q(\theta)^N \delta_l^{n_l} \delta_h^{n_{ch}} \big(\delta_l + (1-\eta)\theta q(\theta)\big)^{n_{sh}} \\ \cdot \quad & \exp\big[-\eta\theta q(\theta)(DU1 - DJ2) - \theta q(\theta)(DU2 + DU3 + DJ2)\big] \\ \cdot \quad & \exp\big[-\delta \sum_{i=1}^{N} DJ_i\big] \cdot (2\pi)^{-3N/2} |\mathbf{Q}|^{1/2} \exp\big[-(\mathbf{e} - \mathbf{Z}\boldsymbol{\gamma})' \, \mathbf{Q} \, (\mathbf{e} - \mathbf{Z}\boldsymbol{\gamma})/2\big] \\ \cdot \quad & \prod_{E=1}^{4} \pi_{E,l}^{m_{E,l}} \cdot \pi_{E,h}^{m_{E,h}}, \end{aligned} \tag{3.15}$$

where ω is the vector of parameters.

As pointed out in section (3.1), for some individuals in the sample the durations of unemployment search DU_i are not observed because they were already employed by the week of school leaving. The probit regression of the binary variable equal to one if individual was employed by the week of school leaving, and equal zero otherwise has shown that being already employed by the week of school leaving is not related to the observable measures of skill level, such as AFQT score, IRO or years of education. Therefore, I assume that for individuals who were already employed by the week of school leaving the information on unemployed search duration DU_i

is missing completely at random. Let I_i be an indicator of the missing DU_i, i.e. $I_i = 1$ if DU_i is not observed, and $I_i = 0$ if DU_i is observed. I assume that $p(I_i = 1|DU_i, DJ_i, lnw_i, afqt_i, f1_i, EDU_i, k_i = j, \omega,) = q$ for $i = 1, ..N$, and $j = 1, 2, 3$.

Let $\{DU_i^o\}_{i=1}^{N^o}$ where N^o is the number of individuals for whom the durations of unemployed search are observed denote observations on unemployed search durations subsequently observed, and let $\{DU_i^m\}_{i=1}^{N^m}$ where N^m is a number of individuals for whom the unemployed search durations are not observed denote observations on unemployed search durations subsequently missing. Also, let $\mathbf{I}$ be a vector such that $\mathbf{I} = [I_1, ..., I_N]'$. Then the joint probability density function of the observables subsequently observed, the observables subsequently missing and the missing indicator $\mathbf{I}$ can be written:

$$\begin{aligned}
&p(\{DU_i^o\}_{i=1}^{N^o}, \{DU_i^m\}_{i=1}^{N^m}, \{DJ_i\}_{i=1}^{N}, \mathbf{e}, \mathbf{EDU}, \mathbf{I}|\omega, \mathbf{k}) \\
&= p(\{DU_i^o\}_{i=1}^{N^o}, \{DU_i^m\}_{i=1}^{N^m}, \{DJ_i\}_{i=1}^{N}, \mathbf{e}, \mathbf{EDU}|\omega, \mathbf{k}) \\
&\cdot p(\mathbf{I}|\{DU_i^o\}_{i=1}^{N^o}, \{DU_i^m\}_{i=1}^{N^m}, \{DJ_i\}_{i=1}^{N}, \mathbf{e}, \mathbf{EDU}, \omega, \mathbf{k}) \\
&= \prod_{i=1}^{N} p(DU_i^o|\omega, k_i)^{1-I_i} p(DU_i^m|\omega, k_i)^{I_i} p(lnw_i|\omega, k_i)(afqt_i|\omega, k_i) p(f1_i|\omega, k_i) \\
&\cdot p(EDU_i|\omega, k_i) \cdot q^{N_m} \cdot (1-q)^{N_o}. \qquad (3.16)
\end{aligned}$$

Then the joint probability density function of the observables subsequently observed and the missing indicator $\mathbf{I}$ can be obtained by integration of the probability density function in (3.16) over the durations of unemployment subsequently missing:

$$
\begin{aligned}
& p(\{DU_i^o\}_{i=1}^{N^o}, \{DJ_i\}_{i=1}^{N}, \mathbf{e}, \mathbf{EDU}, \mathbf{I}|\omega, \mathbf{k}) \\
= \; & \prod_{i=1}^{N} \int p(DU_i^o|\omega, k_i)^{1-I_i} p(DU_i^m|\omega, k_i)^{I_i} p(lnw_i|\omega, k_i)(afqt_i|\omega, k_i) p(f1_i|\omega, k_i) \\
\cdot \; & p(EDU_i|\omega, k_i) dDU_i^m \cdot q^{N_m} \cdot (1-q)^{N_o} \\
= \; & \eta^{n_l^o} \theta q(\theta)^{N^o} \delta_l^{n_l} \delta_h^{n_{ch}} \big(\delta_l + (1-\eta)\theta q(\theta)\big)^{n_{sh}} \\
\cdot \; & \exp\big[-\eta\theta q(\theta)(DU1^o - DJ2) - \theta q(\theta)(DU2^o + DU3^o + DJ2)\big] \\
\cdot \; & \exp\big[-\delta \sum_{i=1}^{N} DJ_i\big] \cdot (2\pi)^{-3N/2} |\mathbf{Q}|^{1/2} \exp\big[-(\mathbf{e} - \mathbf{Z}\boldsymbol{\gamma})' \, \mathbf{Q} \, (\mathbf{e} - \mathbf{Z}\boldsymbol{\gamma})/2\big] \\
\cdot \; & \prod_{E=1}^{4} \pi_{E,l}^{m_{E,l}} \cdot \pi_{E,h}^{m_{E,h}} \cdot q^{N_m} \cdot (1-q)^{N_o},
\end{aligned}
\tag{3.17}
$$

where $n_l^o = \sum_{i=1}^{N} \Delta(k_i, 1) \cdot (1 - I_i)$ and $DUj^o = \sum_{i:I_i=0}^{N} (DU_i^o \Delta(k_i, j))$, $j = 1, 2, 3$. Thus, n_l^o is the number of times in the sample that the unemployment duration is not missing and the state $k_i = 1$ occurs, and DUj^o is the sum of unemployment durations of individuals who have been assigned state $k_i = j$ and have non-missing unemployment durations.

Let $\mathbf{h}$ denote the vector of state-specific precisions of log wages, AFQT scores and IRO:

$$
\mathbf{h} = [h_{w,1}, h_{w,2}, h_{w,3}, h_{afqt,l}, h_{afqt,h}, h_{f1,s}, h_{f1,c}]'. \tag{3.18}
$$

Also, let $\boldsymbol{\pi}_l$ denote the parameters of the distribution of EDU_i of individuals who have been assigned state $k_i = 1$, i.e $\boldsymbol{\pi}_l = [\pi_{1,l}, \pi_{2,l}, \pi_{3,1}, \pi_{4,1}]'$. Similarly, let $\boldsymbol{\pi}_h$ denote the parameters of the distribution of EDU of individuals who have been assigned state $k_i = 2$ or $k_i = 3$, i.e $\boldsymbol{\pi}_h = [\pi_{1,h}, \pi_{2,h}, \pi_{3,h}, \pi_{4,h}]'$. Thus, the vector of parameters

ω is:

$$\omega = [\theta q(\theta), \eta, \delta_s, \delta_c, \boldsymbol{\gamma}', \mathbf{h}', b, y_{s,l}, y_{s,h}, y_{c,h}, \kappa, \beta, \boldsymbol{\pi}'_l, \boldsymbol{\pi}'_h, r, q]'. \tag{3.19}$$

The productivity parameters $y_{s,l}$, $y_{s,h}$, $y_{c,h}$, as well as b and κ can be recovered through the system of equations which consists of equations (2.15), (2.18), (2.26), (2.27). Equations (2.15) and (2.18) determine wages in the equilibrium of the model, and equations (2.26) and (2.27) are free entry conditions for firms in the equilibrium. To recover the productivity parameters $y_{s,l}$, $y_{s,h}$, $y_{c,h}$ and b and κ through equations (2.15), (2.18), (2.26) and (2.27) the functional form of the matching function $m(.,.)$ is needed to be assumed. I assume the Cobb-Douglas specification of the matching function: $m(v_s+v_c, u_l+u_h+e_{s,h}) = 2\cdot(v_s+v_c)^{\frac{1}{2}}\cdot(u_l+u_h+e_{s,h})^{\frac{1}{2}}$. It is easy to shown that these five equations constitute a system of linear equations in five unknowns $y_{s,l}$, $y_{s,h}$, $y_{c,h}$, b and κ conditional on other elements of ω.

3.3 Bayesian Inference

3.3.1 Prior Distributions

To obtain the joint posterior distribution of parameters of interest the the empirical model must be completed with the specification of prior distribution of ω and $\mathbf{k}$. I assume that the discount rate r is .0006, which at the period length of one week implies the yearly discount rate of about 3%. The discount rate is often treated as a known fixed parameters in the structural estimation of search and matching models because the identification of this parameters from the data on durations and wages is difficult. For example, the papers of Flinn (2002), Garcia-Perez (2006) and

Christensen, Lentz, Mortensen, Neumann, and Werwatz (2005) treat the discount rate as a known fixed parameter in the estimation of structural search models.

The following joint prior distribution of $[\beta, \mu, \eta, \theta q(\theta), \delta_s, \delta_c, \boldsymbol{\gamma}', \mathbf{h}', \boldsymbol{\pi}_l', \boldsymbol{\pi}_h']$ is specified:

$$
\begin{aligned}
& p(\beta, \mu, \eta, \theta q(\theta), \delta_s, \delta_c \boldsymbol{\gamma}, \mathbf{h}, \boldsymbol{\pi}_l', \boldsymbol{\pi}_h') = \\
& p(\beta)p(\mu)p(\eta)p(\theta q(\theta))p(\delta_s)p(\delta_c)p(\boldsymbol{\gamma})p(\mathbf{h}p(\boldsymbol{\pi}_l)p(\boldsymbol{\pi}_h) \\
\cdot \quad & I_{\mathbf{S}}([\beta, r, \mu, \eta, \theta q(\theta), \delta_l, \delta_h, \boldsymbol{\gamma}']'), \qquad (3.20)
\end{aligned}
$$

where $I_{\mathbf{A}}(\mathbf{x})$ defines an indicator function, such that $I_{\mathbf{A}}(\mathbf{x}) = 1$ if $\mathbf{x} \in \mathbf{A}$ and $I_{\mathbf{A}}(\mathbf{x}) = 0$ otherwise, and $\mathbf{S}$ is the subset of parameter space where the productivity parameters $y_{s,l}$, $y_{s,h}$, $y_{c,h}$ and the unemployment income parameter b satisfy the assumptions of the model, in particular $max\{y_{s,l}, y_{s,h}\} < y_{c,h}$ and $min\{y_{s,l}, y_{s,h}\} > b$, and where the parameters are consistent with firms' willingness to open complex vacancies as stated in (2.35).

I specify that $p(\beta)$, $p(\mu)$, $p(\eta)$ are probability density functions of beta distribution, $p(\theta q(\theta))$, $p(\delta_s)$, $p(\delta_c)$ are probability density functions of gamma distribution, $p(\mathbf{h})$ is a product of probability density functions of gamma distribution for each component of $\mathbf{h}$, $p(\boldsymbol{\gamma})$ is a probability density function of normal distribution truncated to the set $\mathbf{B}\boldsymbol{\gamma} < \mathbf{0}$, where

$$\underset{4\times 7}{\mathbf{B}} = \begin{pmatrix} 1 & 0 & -1 & 0 & 0 & 0 & 0 \\ 0 & 1 & -1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & -1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & -1 \end{pmatrix}.$$

As has been shown in section 2.4.6, in a policy-free equilibrium the wage on complex jobs is always higher than the wage of a high-skilled worker on a simple jobs, and that the wage on complex job is higher than the wage of a low-skilled worker on a simple job when the present discounted value of being unemployed of a high-skilled worker is greater than that of a low-skilled worker. The restriction $\mathbf{B}\boldsymbol{\gamma} < \mathbf{0}$ summarizes these restrictions on the parameters of wage distribution, as well as the identifying assumptions about the distributions of AFQT scores and IRO discussed in section 3.2.3, in particular that the mean of AFQT score of high-skilled workers is higher than that of low-skilled workers and that the mean of IRO of complex jobs is higher than that of simple jobs. The probability density functions $p(\boldsymbol{\pi}_l)$ and $p(\boldsymbol{\pi}_h)$ are those of a Dirichlet distribution.

Thus:

$$p(\beta) \propto \beta^{(\alpha_{\beta 1}-1)}(1-\beta)^{(\alpha_{\beta 2}-1)}, \tag{3.21}$$

$$p(\mu) \propto \mu^{(\alpha_{\mu 1}-1)}(1-\mu)^{(\alpha_{\mu 2}-1)}, \tag{3.22}$$

$$p(\eta) \propto \eta^{(\alpha_{\eta 1}-1)}(1-\eta)^{(\alpha_{\eta 2}-1)}, \tag{3.23}$$

$$p(\theta q(\theta)) \propto \theta q(\theta)^{(\underline{\nu}_\theta-2)/2} \exp(-\underline{s}_\theta^2 \theta q(\theta)/2), \tag{3.24}$$

$$p(\delta_s) \propto \delta_s^{(\underline{\nu}_{\delta_s}-2)/2} \exp(-\underline{s}^2_{\delta_s}\delta_l/2), \tag{3.25}$$

$$p(\delta_c) \propto \delta_c^{(\underline{\nu}_{\delta_c}-2)/2} \exp(-\underline{s}^2_{\delta_c}\delta_h/2), \tag{3.26}$$

$$\begin{aligned} p(\mathbf{h}) &\propto h_{w,1}^{(\underline{\nu}_1-2)/2} \cdot h_{w,2}^{(\underline{\nu}_2-2)/2} \cdot h_{w,3}^{(\underline{\nu}_3-2)/2} \cdot h_{afqt,l}^{(\underline{\nu}_4-2)/2} \cdot h_{afqt,h}^{(\underline{\nu}_5-2)/2} \cdot h_{f1,s}^{(\underline{\nu}_6-2)/2} \cdot h_{f1,c}^{(\underline{\nu}_7-2)/2} \quad (3.27) \\ &\cdot \exp[-\frac{1}{2}(\underline{s}_1^2 h_{w,1} + \underline{s}_2^2 h_{w,2} + \underline{s}_3^2 h_{w,3} + \underline{s}_4^2 h_{afqt,l} + \underline{s}_5^2 h_{afqt,h} + \underline{s}_6^2 h_{f1,s} + \underline{s}_7^2 h_{f1,c})] \\ p(\boldsymbol{\gamma}) &\propto \exp\big[-(\boldsymbol{\gamma}-\underline{\boldsymbol{\gamma}})'\underline{\mathbf{H}}(\boldsymbol{\gamma}-\underline{\boldsymbol{\gamma}})/2\big] \cdot I_{(-\infty,0)}(\mathbf{B}\boldsymbol{\gamma}), \quad (3.28) \end{aligned}$$

$$p(\boldsymbol{\pi}_l) \propto \prod_{E=1}^{4} \pi_{E,l}^{(\alpha_{\pi_{E,l}}-1)}, \tag{3.29}$$

$$p(\boldsymbol{\pi}_h) \propto \prod_{E=1}^{4} \pi_{E,h}^{(\alpha_{\pi_{E,h}}-1)}. \tag{3.30}$$

The prior conditional on ω distribution of the state assignment $\mathbf{k}$ is multinomial:

$$p(k_i = j|\omega) = \mu^{\Delta(j,1)}[(1-\mu)\eta]^{\Delta(j,2)}[(1-\mu)(1-\eta)]^{\Delta(j,3)} \tag{3.31}$$

$$i = 1, ..., N; j = 1, 2, 3,$$

where $\Delta(a, b)$ is the Kroneker delta function: $\Delta(a, b) = 1$ if $a = b$ and $\Delta(a, b) = 0$ otherwise.

If the prior distribution of probability to have missing duration of unemployment DU_i q is independent of the prior distribution of the remaining parameters in ω, then the observed collection of data $\{DU_i^o\}_{i=1}^{N^o}$,$\{DJ_i\}_{i=1}^{N}$, $\mathbf{e}$, $\mathbf{EDU}$ is an ancillary statistic with respect to q using the definition given in Geweke (2005) in section 2.2.2. To simplify inference, I assume that the prior distribution of q is independent of the prior distribution of the remaining parameters of ω. This assumption allows me not to develop the posterior inference for q because the counterfactual labor market outcomes of workers of different skill levels which constitute the vector of interest of this analysis do not depend on q.

3.3.2 Posterior Inference

Let $\mathbf{D}$ denote the collection of the observed data $\{DU_i^o\}_{i=1}^{N^o}$, $\{DJ_i\}_{i=1}^{N}$, $\mathbf{e}$, $\mathbf{EDU}$, $\mathbf{I}$. Using Bayes rule, the joint posterior distribution of ω and $\mathbf{k}$ $p(\omega, \mathbf{k}|\mathbf{D})$ is proportional to the product of $p(\mathbf{D}|\mathbf{k}, \omega,)$ given in (3.17), $p(\mathbf{k}|\omega)$ given in (3.7) and $p(\omega)$ given in (3.20). To sample from this distribution I use the Metropolis-Hastings within Gibbs algorithm. This algorithm iteratively draws from the complete conditional posterior distributions of the parameters and the assignment of latent states. The successive sampling from the complete conditional posterior distributions converges to the sampling from the joint posterior distribution of the parameters under certain regularity conditions (Chib and Greenberg (1995)). The algorithm developed in this section is based on the algorithm for Bayesian inference in normal mixture linear models developed in Geweke (2005).

Let ω_{-x} denote a vector which includes all elements of ω except x. The Gibbs sampler proceeds in the following steps:

1. Sample the vector of state-specific means of log-wages, AFQT scores and IRO $\boldsymbol{\gamma}$:

$$\begin{aligned}\boldsymbol{\gamma}|(\omega_{-\boldsymbol{\gamma}}, \mathbf{k}, \mathbf{D}) \quad &\propto \quad exp\left[(\boldsymbol{\gamma} - \overline{\boldsymbol{\gamma}})'\overline{\mathbf{H}}(\boldsymbol{\gamma} - \overline{\boldsymbol{\gamma}})/2\right] \\ &\cdot \quad I_{(-\infty,0)}(\mathbf{B}\boldsymbol{\gamma}) \cdot I_{\mathbf{S}}([\beta, r, \mu, \eta, \theta q(\theta), \delta_s, \delta_c, \boldsymbol{\gamma}']'),\end{aligned}$$

where

$$\overline{\mathbf{H}} = \underline{\mathbf{H}} + \mathbf{Z}'\mathbf{QZ}, \qquad \overline{\gamma} = \overline{\mathbf{H}}^{-1}\big[\underline{\mathbf{H}}\underline{\boldsymbol{\gamma}} + \mathbf{ZQe}\big].$$

The draws from this distribution are made one element of $\boldsymbol{\gamma}$ at a time by successively drawing from the conditional posterior distribution of $\gamma_j|[\boldsymbol{\gamma}_{-\gamma_j}, \omega_{-}\boldsymbol{\gamma}, \mathbf{D}]$ which is obtained using Theorem 5.3.1 in Geweke (2005):

$$\begin{aligned} p(\gamma_j|\boldsymbol{\gamma}_{-\gamma_j}, \omega_{-}\boldsymbol{\gamma}, \omega_{-}\boldsymbol{\gamma}, \mathbf{D}) \;\; &\propto \;\; exp[-\overline{h}_{jj}(\gamma_j - \overline{\gamma}_j^*)^2/2] \cdot I_{(-\infty,0)}(\mathbf{B}\boldsymbol{\gamma}) \\ &\cdot \;\; I_{\mathbf{S}}([\beta, r, \mu, \eta, \theta q(\theta), \delta_s, \delta_c, \boldsymbol{\gamma}']'), \end{aligned}$$

where

$$\overline{\gamma}_j^* = \overline{\gamma}_j - \overline{h}_{jj}^{-1} \sum_{i \neq j} \overline{h}_{ji}(\gamma_i - \overline{\gamma}_i).$$

To draw from this distribution I use the Metropolis-Hastings algorithm:

1.1. Draw a candidate $\widetilde{\gamma}_j$ from the $N(m_j, \sigma_j^2)$ truncated to the set $\mathbf{B}\boldsymbol{\gamma} < 0$, where

$$\begin{aligned} m_j \;\; &= \;\; \overline{\gamma}_j^{(n-1)} - [\overline{h}_{jj}^{(n-1)}]^{-1} \sum_{i<j} \overline{h}_{ji}^{(n-1)}(\gamma_i^{(n)} - \overline{\gamma}_i^{(n-1)}) \\ &- \;\; [\overline{h}_{jj}^{(n-1)}]^{-1} \sum_{i>j} \overline{h}_{ji}^{(n-1)}(\gamma_i^{(n-1)} - \overline{\gamma}_i^{(n-1)}), \\ \sigma_j^2 \;\; &= \;\; [\overline{h}_{jj}^{(n-1)}]^{-1}. \end{aligned}$$

This amounts to drawing $\widetilde{\gamma}_j$ from the $N(m_j, \sigma_j^2)$ truncated to the sets $(-\infty, \gamma_3^{(n-1)})$ for $j = 1, 2$, $(max\{\gamma_1^{(n)}, \gamma_2^{(n)}\}, \infty)$ for $j = 3$, $(-\infty, \gamma_5^{(n-1)})$ for $j = 4$, (γ_4^n, ∞) for $j = 5$, $(-\infty, \gamma_7^{(n-1)})$ for $j = 6$, (γ_6^n, ∞) for $j = 7$.

The draws from these truncated normal distributions are made using the efficient algorithm developed in Geweke (1991).

1.2. Accept the candidate draw $\widetilde{\gamma}_j$ as $\gamma_j^{(n)}$ if

$$I_{\mathbf{S}}([\beta^{(n-1)}, r, \mu^{(n-1)}, \eta^{(n-1)}, \theta q(\theta)^{(n-1)}, \delta_s^{(n-1)}, \delta_c^{(n-1)}, [\boldsymbol{\gamma}_{<j}^{(n)}, \widetilde{\gamma}_j, \boldsymbol{\gamma}_{>j}^{(n-1)}]]) = 1.$$

Otherwise set $\gamma_j^{(n)}$ to $\gamma_j^{(n-1)}$.

2. Sample a vector of state-specific precisions of log-wages, AFQT scores and IRO:

$$\Big[\underline{s}_j^2 + \sum_{i=1}^{N}(lnw_i - w_{k_i}^*)^2\Delta(k_i, j)\Big]h_{w,j}|(\omega_{-h_{w,j}}, \mathbf{k}, \mathbf{D}) \sim \chi^2(\underline{\nu}_j + \sum_{i=1}^{N}\Delta(k_i, j))$$

for $j = (1, 2, 3)$,

$$\Big[\underline{s}_4^2 + \sum_{i=1}^{N}(afqt_i - x_l)^2\Delta(k_i, 1)\Big]h_{afqt,l}|(\omega_{-h_{afqt,l}}, \mathbf{k}, \mathbf{D}) \sim \chi^2(\underline{\nu}_4 + n_l),$$

$$\Big[\underline{s}_5^2 + \sum_{i=1}^{N}(afqt_i - x_h)^2(\Delta(k_i, 2) + \Delta(k_i, 3))\Big]h_{afqt,h}|(\omega_{-h_{afqt,h}}, \mathbf{k}, \mathbf{D})$$
$$\sim \chi^2(\underline{\nu}_5 + n_{sh} + n_{ch}),$$

$$\Big[\underline{s}_6^2 + \sum_{i=1}^{N}(f1_i - y_s)^2(\Delta(k_i, 1) + \Delta(k_i, 2))\Big]h_{f1,s}|(\omega_{-h_{f1,s}}, \mathbf{k}, \mathbf{D})$$
$$\sim \chi^2(\underline{\nu}_6 + n_l + n_{sh}),$$

$$\Big[\underline{s}_7^2 + \sum_{i=1}^{N}(f1_i - y_c)^2\Delta(k_i, 3)\Big]h_{f1,c}|(\omega_{-h_{f1,c}}, \mathbf{k}, \mathbf{D}) \sim \chi^2(\underline{\nu}_7 + n_{ch}),$$

3. Sample the job arrival rate $\theta q(\theta)$:

$$
\begin{aligned}
& p(\theta q(\theta)|\omega_{-\theta q(\theta)}, \mathbf{k}, \mathbf{D}) \\
& \propto \theta q(\theta)^{(\underline{\nu}_\theta + 2N^o - 2)/2} \exp\Big[- \theta q(\theta)[\underline{s}_\theta^2/2 + \eta DU1^o + DU2^o + DU3^o\Big] \\
& \cdot(\delta_s + (1-\eta)\theta q(\theta))^{n_{sh}} \exp[-(\delta_s + (1-\eta)\theta q(\theta))DJ2] \\
& \cdot I_{\mathbf{S}}([\beta, r, \mu, \eta, \theta q(\theta), \delta_s, \delta_c, \boldsymbol{\gamma}']') \\
= \;& k_1(\theta q(\theta)|\omega_{-\theta q(\theta)}, \mathbf{k}, \mathbf{D}) \cdot k_2(\theta q(\theta)|\omega_{-\theta q(\theta)}, \mathbf{k}, \mathbf{D}) \\
\cdot \;& I_{\mathbf{S}}([\beta, r, \mu, \eta, \theta q(\theta), \delta_s, \delta_c, \boldsymbol{\gamma}']').
\end{aligned}
$$

The kernel of the posterior distribution of $\theta q(\theta)$ is a product of kernels of gamma density $k_1(\theta q(\theta)|.)$, shifted gamma density $k_2(\theta q(\theta)|.)$ and the indicator function $I_{\mathbf{S}}(.)$. To draw from this distribution I employ the Metropolis-Hastings algorithm:

1.1. Draw a candidate $\widetilde{\theta q(\theta)}$ from $N(m, \sigma^2)$ truncated to $(0, \infty)$, where m is the mode of the conditional posterior distribution of $\theta q(\theta)$, and σ^2 is negative of the inverse of second derivative of the probability density function of the posterior distribution of $\theta q(\theta)$ evaluated at mode.

1.2. Accept the candidate draw $\widetilde{\theta q(\theta)}$ as $\theta q(\theta)^{(n)}$ with the probability:

$$
\begin{aligned}
\alpha \;&=\; \frac{k_1(\widetilde{\theta q(\theta)}|.) \cdot k_2(\widetilde{\theta q(\theta)}|.) \cdot exp[(\theta q(\theta)^{(n-1)} - m)^2/2\sigma^2]}{k_1(\theta q(\theta)^{(n-1)}|.) \cdot k_2(\theta q(\theta)^{(n-1)}|.) \cdot exp[(\widetilde{\theta q(\theta)} - m)^2/2\sigma^2]} \\
&\cdot \;\; I_{\mathbf{S}}([\beta^{(n-1)}, r, \mu^{(n-1)}, \eta^{(n-1)}, \widetilde{\theta q(\theta)}, \delta_s^{(n-1)}, \delta_c^{(n-1)}, \boldsymbol{\gamma}^{(n)'}]').
\end{aligned}
$$

4. Sample the rate of job destruction of simple jobs δ_s:

$$\begin{aligned} & p(\delta_s|\omega_{-\delta_s}, \mathbf{k}, \mathbf{D}) \propto \\ & \propto \delta_s^{(\underline{\nu}_{\delta_s}+2n_l-2)/2} \exp\Big[-\delta_s(DJ_1 + DJ2)\Big] \\ & \cdot(\delta_s + (1-\eta)\theta q(\theta))^{n_{sh}} \exp[-(\delta_s + (1-\eta)\theta q(\theta))\underline{s}^2_{\delta_s}/2] \\ & \cdot I_{\mathbf{S}}([\beta, r, \mu, \eta, \theta q(\theta), \delta_s, \delta_c, \boldsymbol{\gamma}']') \\ = \ & k_1(\delta_s|\omega_{-\delta_s}, \mathbf{k}, \mathbf{D}) \cdot k_2(\delta_s|\omega_{-\delta_s}, \mathbf{k}, \mathbf{D}) \cdot I_{\mathbf{S}}([\beta, r, \mu, \eta, \theta q(\theta), \delta_s, \delta_c, \boldsymbol{\gamma}']'), \end{aligned}$$

where $k_1(\delta_s|.)$ is a kernel of gamma density, and $k_2(\delta_s|.)$ is a kernel of shifted gamma density. To sample from this distribution I employ the Metropolis-Hastings algorithm:

1.1. Draw a candidate $\widetilde{\delta_s}$ from $N(m, \sigma^2)$ truncated to $(0, \infty)$, where m is the mode of of the conditional posterior distribution of δ_s, and σ^2 is the is negative of the inverse of second derivative of the probability density function of the posterior distribution of δ_s evaluated at mode.

1.2. Accept the candidate draw $\widetilde{\delta_s}$ as $\delta_s^{(n)}$ with the probability:

$$\begin{aligned} \alpha &= \frac{k_1(\widetilde{\delta_s}|.) \cdot k_2(\widetilde{\delta_s}|.) \cdot exp[(\delta_s)^{(n-1)} - m)^2/2\sigma^2]}{k_1(\delta_s^{(n-1)}|.) \cdot k_2(\delta_s^{(n-1)}|.) \cdot exp[(\widetilde{\delta_s} - m)^2/2\sigma^2]} \\ &\cdot \quad I_{\mathbf{S}}([\beta^{(n-1)}, r, \mu^{(n-1)}, \eta^{(n-1)}, \theta q(\theta)^{(n)}, \widetilde{\delta_s}, \delta_c^{(n-1)}, \boldsymbol{\gamma}^{(n)'}]'). \end{aligned}$$

5. Sample the rate of job destruction of complex jobs:

$$\begin{aligned} p(\delta_c|\omega_{-\delta_c}, \mathbf{k}, \mathbf{D}) \ \propto \ & \delta_c^{(\underline{\nu}_{\delta_c}+2n_{ch}-2)/2} \cdot \exp\Big[-\delta_c(DJ_3)\Big] \\ \cdot \ & I_{\mathbf{S}}([\beta, r, \mu, \eta, \theta q(\theta), \delta_s, \delta_c, \boldsymbol{\gamma}']'). \end{aligned}$$

To sample from this distribution I employ the Metropolis-Hastings algorithm. I draw a candidate $\widetilde{\delta}_c$ from $Gamma(\underline{\nu}_{\delta_c} + n_{ch}, 1/DJ_3)$ and set $\delta_c^{(n)} = \widetilde{\delta}_c$ if

$$I_{\mathbf{S}}([\beta^{(n-1)}, r, \mu^{(n-1)}, \eta^{(n-1)}, \theta q(\theta)^{(n)}, \delta_s^{(n)}, \widetilde{\delta}_c, \boldsymbol{\gamma}^{(n)\prime}]') = 1.$$

$\delta_c^{(n)}$ is set to $\delta_c^{(n-1)}$ otherwise.

6. Sample the fraction of simple vacancies in a mass of vacancies η:

$$\begin{aligned}
& p(\eta|\omega_{-\eta}, \mathbf{k}, \mathbf{D}) \propto \eta^{(\alpha_{\eta 1}+n_{sh}-1)}(1-\eta)^{(\alpha_{\eta 2}+n_{ch}-1)} \\
& \cdot(\delta_s + (1-\eta)\theta q(\theta))^{n_{sh}} \exp[-(\delta_s + (1-\eta)\theta q(\theta))DJ2] \\
& \cdot\eta^{n_l^o} \exp[-\eta\theta q(\theta)DU1^o] \cdot I_{\mathbf{S}}([\beta, r, \mu, \eta, \theta q(\theta), \delta_s, \delta_c, \boldsymbol{\gamma}']') \\
= \;& k_1(\eta|\omega_{-\eta}, \mathbf{k}, \mathbf{D}) \cdot k_2(\eta|\omega_{-\eta}, \mathbf{k}, \mathbf{D}) \cdot k_3(\eta|\omega_{-\eta}, \mathbf{k}, \mathbf{D}) \\
\cdot \;& I_{\mathbf{S}}([\beta, r, \mu, \eta, \theta q(\theta), \delta_s, \delta_c, \boldsymbol{\gamma}']'),
\end{aligned}$$

where $k_1(\eta|.)$ is a kernel of a beta density, $k_2(\eta|.)$ is a kernel of a shifted gamma density, $k_3(\eta)$ is a kernel of a gamma density. To sample from this distribution I employ the Metropolis-Hastings algorithm:

1.1. Draw a candidate $\widetilde{\eta}$ from $beta(\alpha_{\eta 1} + n_{sh}, \alpha_{\eta 2} + n_{ch})$.

1.2. Accept the candidate draw $\widetilde{\eta}$ as $\eta^{(n)}$ with the probability:

$$\begin{aligned}
\alpha &= \frac{k_2(\widetilde{\eta}|.) \cdot k_3(\widetilde{\eta}|.)}{k_2(\eta^{(n-1)}|.) \cdot k_3(\eta^{(n-1)}|.)} \\
&\cdot \; I_{\mathbf{S}}([\beta^{(n-1)}, r, \mu^{(n-1)}, \widetilde{\eta}, \theta q(\theta)^{(n)}, \delta_s^{(n)}, \delta_c^{(n)}, \boldsymbol{\gamma}^{(n)\prime}]').
\end{aligned}$$

7. Sample the fraction of low-skilled workers μ:

$$\mu|(\omega_{-\mu}, \mathbf{k}, \mathbf{D}) \propto \mu^{\alpha_{\mu_1}+n_l-1}(1-\mu)^{\alpha_{\mu_2}+n_{sh}+n_{ch}-1} \cdot I_{\mathbf{S}}([\beta, r, \mu, \eta, \theta q(\theta), \delta_s, \delta_c, \boldsymbol{\gamma}']').$$

To sample from this distribution I employ the Metropolis-Hastings algorithm. I draw a candidate $\widetilde{\mu}$ from $beta(\alpha_{\mu_1} + n_l, \alpha_{\mu_2} + n_{sh} + n_{ch})$ and set $\mu^{(n)} = \widetilde{\mu}$ if

$$I_{\mathbf{S}}([\beta^{(n-1)}, r, \widetilde{\mu}, \eta^{(n)}, \theta q(\theta)^{(n)}, \delta_s^{(n)}, \widetilde{\delta_c}, \boldsymbol{\gamma}^{(n)\prime}]') = 1.$$

$\mu^{(n)}$ is set to $\mu^{(n-1)}$ otherwise.

8. Sample worker's surplus share β:

$$p(\beta|\omega_{-\beta}, \mathbf{k}, \mathbf{D}) = p(\beta) \cdot I_{\mathbf{S}}([\beta, r, \mu, \eta, \theta q(\theta), \delta_s, \delta_c, \boldsymbol{\gamma}']').$$

To sample from this distribution I employ the Metropolis-Hastings algorithm. I draw a candidate $\widetilde{\beta}$ from $beta(\alpha_{\beta_1}, \alpha_{\beta_2})$ and set $\beta^{(n)} = \widetilde{\beta}$ if

$$I_{\mathbf{S}}([\widetilde{\beta}, r, \mu^{(n)}, \eta^{(n)}, \theta q(\theta)^{(n)}, \delta_s^{(n)}, \widetilde{\delta_c}, \boldsymbol{\gamma}^{(n)\prime}]') = 1.$$

$\beta^{(n)}$ is set to $\beta^{(n-1)}$ otherwise.

9. Sample the vector of parameters of distribution of EDU of low-skilled workers:

$$\boldsymbol{\pi}_l|\omega_{-\boldsymbol{\pi}_l}, \mathbf{k}, \mathbf{D} \sim Dirichlet(\alpha_{\pi_{E,l}} + m_{E,l}), E = 1, ..., 4. \tag{3.32}$$

10. Sample the vector of parameters of distribution of EDU of high-skilled workers:

$$\boldsymbol{\pi}_h|\omega_{-\boldsymbol{\pi}_h}, \mathbf{k}, \mathbf{D} \sim Dirichlet(\alpha_{\pi_{E,h}} + m_{E,l}), E = 1, ..., 4. \tag{3.33}$$

11. Sample the latent state k_i for individuals whose unemployed search duration is not observed:

$$\begin{aligned} & p(k_i = 1|\omega, \mathbf{k}, \mathbf{D}) \propto \mu\Big(\delta_s \exp[-\delta_s DJ_i]\Big) \cdot (h_{w,1} h_{afqt,l} h_{f1,s})^{1/2} \\ \cdot \quad & \exp(\frac{1}{2}[h_{w,l}(lnw_i - w_1^*)^2 + h_{afqt,l}(afqt_i - x_l)^2 + h_{f1,s}(f1_i - y_s)^2]) \\ \cdot \quad & (\pi_{E,l} \cdot \Delta(EDU_i, E)), \end{aligned}$$

$$p(k_i = 2|\omega, \mathbf{k}, \mathbf{D}) \propto (1-\mu)\eta \cdot (\delta_s + (1-\eta)\theta q(\theta))$$

$$\cdot \quad \exp[-(\delta_s + (1-\eta)\theta q(\theta))DJ_i] \cdot (h_{w,2}h_{afqt,h}h_{f1,s})^{1/2}$$

$$\cdot \quad \exp(\frac{1}{2}[(h_{w,2}(lnw_i - w^*_{sh})^2 + h_{afqt,h}(afqt_i - x_h)^2 h_{f1,s}(f1_i - y_s)^2)])$$

$$\cdot \quad (\pi_{E,h} \cdot \Delta(EDU_i, E)),$$

$$p(k_i = 3|\omega, \mathbf{k}, \mathbf{D}) \propto (1-\mu)(1-\eta) \cdot \delta_c \exp[-\delta_c DJ_i] \cdot (h_{w,3}h_{afqt,h}h_{f1,c})^{1/2}$$

$$\cdot \quad \exp(\frac{1}{2}[h_{w,ch}(lnw_i - w^*_3)^2 + h_{afqt,h}(afqt_i - x_h)^2 + h_{f1,c}(f1_i - y_c)^2])$$

$$\cdot \quad (\pi_{E,h} \cdot \Delta(EDU_i, E)).$$

12. Sample the latent state k_i for individuals whose unemployed search duration is observed:

$$p(k_i = 1|\omega, \mathbf{k}, \mathbf{D}) \propto \mu\Big(\eta\theta q(\theta)\exp[-\eta\theta q(\theta)DU^o_i] \cdot \delta_s \exp[-\delta_s DJ_i]\Big)$$

$$\cdot \quad (h_{w,1}h_{afqt,l}h_{f1,s})^{1/2}$$

$$\cdot \quad \exp(\frac{1}{2}[h_{w,l}(lnw_i - w^*_1)^2 + h_{afqt,l}(afqt_i - x_l)^2 + h_{f1,s}(f1_i - y_s)^2])$$

$$\cdot \quad (\pi_{E,l} \cdot \Delta(EDU_i, E)),$$

$$p(k_i = 2|\omega, \mathbf{k}, \mathbf{D}) \propto (1-\mu)\eta \cdot \theta q(\theta)\exp[-\theta q(\theta)DU_i]$$

$$\cdot \quad (\delta_s + (1-\eta)\theta q(\theta))\exp[-(\delta_s + (1-\eta)\theta q(\theta))DJ_i]$$

$$\cdot \quad (h_{w,2}h_{afqt,h}h_{f1,s})^{1/2}$$

$$\cdot \quad \exp(\frac{1}{2}[(h_{w,2}(lnw_i - w^*_{sh})^2 + h_{afqt,h}(afqt_i - x_h)^2 h_{f1,s}(f1_i - y_s)^2)])$$

$$\cdot \quad (\pi_{E,h} \cdot \Delta(EDU_i, E))$$

$$p(k_i = 3|\omega, \mathbf{k}, \mathbf{D}) \propto (1-\mu)(1-\eta) \cdot \theta q(\theta) \exp[-\theta q(\theta) DU_i] \cdot \delta_c \exp[-\delta_c DJ_i]$$

$$\cdot \quad (h_{w,3} h_{afqt,h} h_{f1,c})^{1/2}$$

$$\cdot \quad \exp(\frac{1}{2}[h_{w,ch}(lnw_i - w_3^*)^2 + h_{afqt,h}(afqt_i - x_h)^2 + h_{f1,c}(f1_i - y_c)^2])$$

$$\cdot \quad (\pi_{E,h} \cdot \Delta(EDU_i, E)).$$

The joint distribution test for detection of errors in simulation algorithms proposed in Geweke (2004) could not reject the null hypothesis that the Matlab code for this posterior simulator is error-free when a Bonferroni test for multiple comparisons and a significance level of 5% were used. The details of the joint distribution test are presented in Appendix.

I specify the following prior distribution of ω:

$$\beta \sim beta(2, 2),$$

$$\mu \sim beta(2, 2),$$

$$\eta \sim beta(2, 2),$$

$$\theta q(\theta) \sim gamma(1/2, 1/2),$$

$$\delta_s \sim gamma(1/2, 1/25),$$

$$\delta_c \sim gamma(1/2, 1/25),$$

$$\underline{\boldsymbol{\gamma}} = (4.97, 4.97, 5.15, -.5, 1, -.5, 1)',$$

$$\underline{\boldsymbol{H}} = diag(1, 1, 1, 1, 1, 1, 1, 1),$$

$$.1 \cdot h_{w,j} \sim \chi^2(2), j = 1, 2, 3,$$

$$1.5 \cdot h_{afqt,l} \sim \chi^2(2),$$

$$1.5 \cdot h_{afqt,h} \sim \chi^2(2),$$

$$2 \cdot h_{f1,s} \sim \chi^2(2),$$

$$2 \cdot h_{f1,c} \sim \chi^2(2),$$

$$\boldsymbol{\pi}_l \sim Dirichlet(.5, .5, .5, .5),$$

$$\boldsymbol{\pi}_h \sim Dirichlet(.5, .5, .5, .5),$$

all subjects to the constraints discussed in section 3.3.1. The prior distributions are chosen so that the means, standard deviations, coefficients of skewness and kurtosis, 10^{th}, 50^{th} and 90^{th} percentiles of the sample durations of unemployment and employment, wages, IRO and AFQT scores are all within the 10^{th} and 90^{th} percentiles of distributions of these statistics obtained from 200 artificial data samples of the same size as the data generated conditional on 200 random draws from the prior.

For the posterior inference I produce 500000 draws from the posterior distribution of ω. I discard the first 30000 draws to eliminate the effect of the initial draw and use the remaining 470000 draws to approximate the posterior distribution of ω. The convergence of the posterior simulation is assessed by formally comparing the means of the elements of ω and of the functions of ω presented in Table 3.3 computed using the first 20% of the sample of draws with the means computed using the last 50% of the sample of draws as suggested in Geweke (1992). For each of these 37 pairs of partial means the null hypothesis that the two partial means are equal could not be rejected at the 10% significance level.

3.4 Results

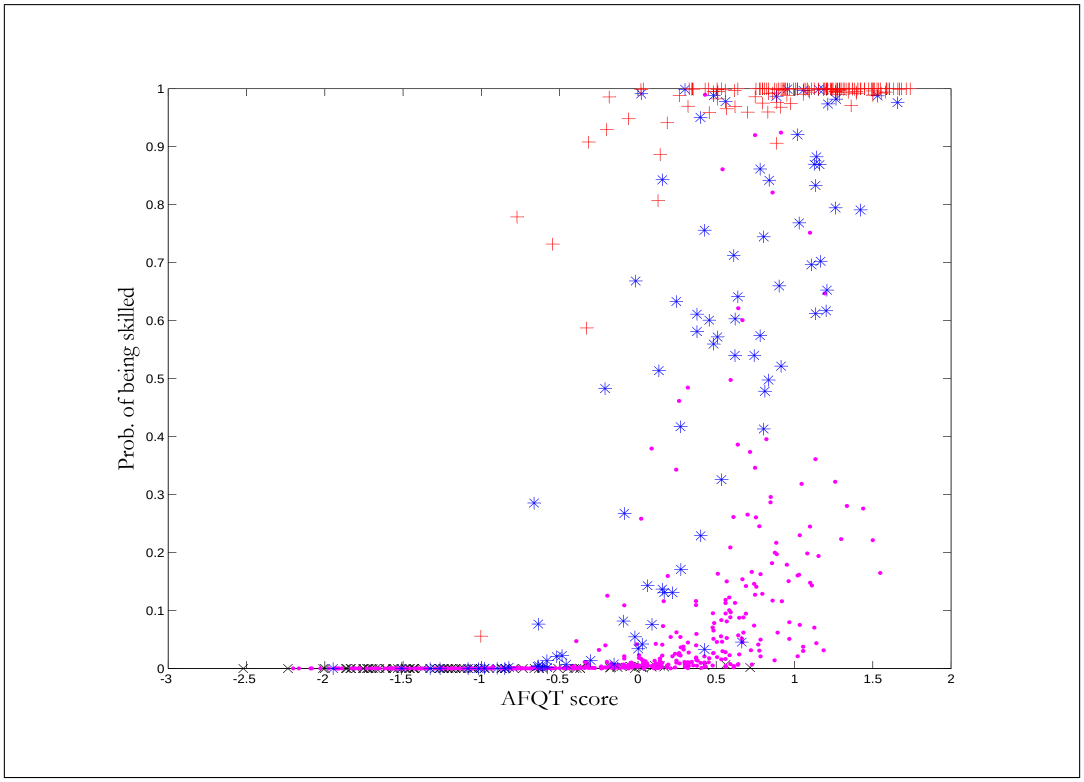
Table 3.3 presents some prior and posterior moments of the vector of parameters ω and of some functions of ω. The sixth column of Table 3.3 contains the relative numerical efficiency (RNE) proposed in Geweke (1992). The RNE indicates the number of iid draws from the posterior distribution that would be required to produce the numerical accuracy of the approximation of posterior moments using the output from the MCMC simulator. The RNE close to unity indicates that the draws produced by the MCMC simulator are close to iid. The RNE below unity indicates that the draws produced by the MCMC simulator are positively correlated, and therefore more draws from the MCMC simulator is required to achieve a specific numerical accuracy compared to the iid simulation. The RNE exceeding unity indicates that the draws produced by the MCMC simulator are negatively correlated, and therefore fewer draws from the MCMC simulator is required to achieve a specific numerical accuracy compared to the iid simulation. For example, the RNE of b is equal .34, indicating that only $.34 \cdot 470000 = 159800$ iid draws from the posterior distribution of b is required to achieve the numerical accuracy of the 470000 draws from the posterior distribution of b produced by the MCMC algorithm described in section 3.3.2.

The results in Table 3.3 suggest that high-skilled workers are about 50% more productive on simple jobs than low-skilled workers. The productivity of a complex job is about 68% higher than the mean productivity of a simple job. In the steady-state of the economy low-skilled workers make about 84% of the pool of unemployed. The posterior mean of the fraction of workers who are low-skilled μ is .73. The posterior mean of the number of high-skilled workers who are mismatched is .03, which implies that about 11% of high-skilled workers are mismatched in the steady state. This number is of the same order of magnitude as the mismatch estimate in Gottschalk and Hansen (2003), who define a non-college occupation as an occupation with college wage premium of less than 10%, and estimate that probability of a college graduate's being in a non-college occupation is about 9% in 1983 wave of CPS.

Because the productivity of high-skilled workers on simple jobs is on average higher than that of low-skilled workers, high-skilled workers earn more on simple jobs than low-skilled workers. Define the average skill premium $\frac{e_{s,h} \cdot w_{s,h} + e_{c,h} \cdot w_{c,h}}{e_{s,h} + e_{c,h}} / w_{s,l} - 1$. The posterior mean of the average skill premium so defined is equal 63%. The model implies that the average unemployment duration of a low-skilled worker is about 47 weeks, and that of a high-skilled workers is about 22 weeks. The expected job duration of a low-skilled worker is about 50 weeks. The expected job duration of a mismatched high-skilled worker is about 22 weeks, and that of a high-skilled worker on a complex job is about 71 weeks. The implied mean job duration of a high-skilled worker is about 63 weeks.

The posterior mean of worker's share of the match surplus β is .549 and the posterior standard deviation is .198. These moments are similar to those of the prior distribution of β which implies that the constraints on parameter space discussed in section 3.3.1 do not provide enough information to update the prior distribution of β substantially. Figure 3.7 shows the estimates of prior and posterior probability densities of β. The green dashed line corresponds to the estimate of the probability

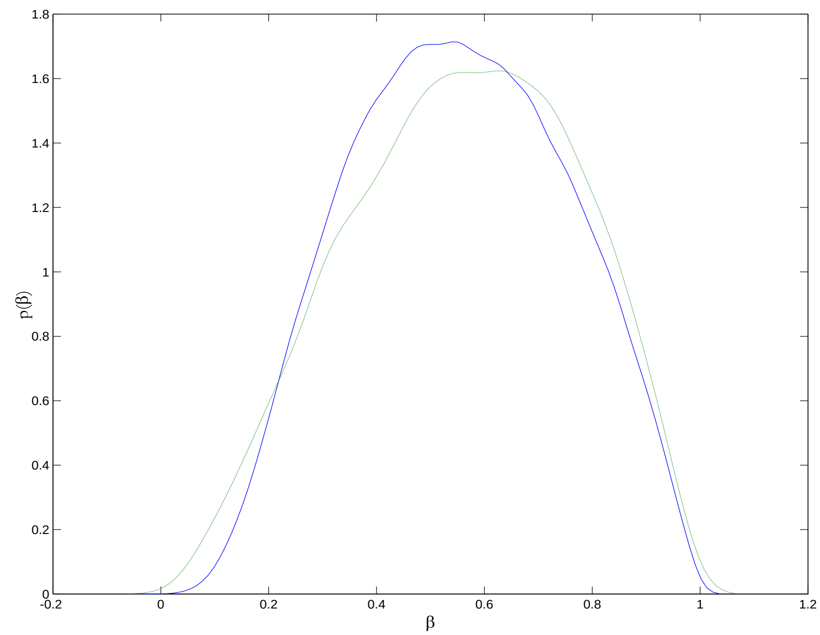
Figure 3.6: Posterior Probability of Being High-Skilled



density of the prior distribution of β, and the blue solid line corresponds to the estimate of the probability density of the posterior distribution of β. The shape of the posterior distribution of β is slightly different than the shape of the prior distribution, but this difference is not enough to produce substantial differences between prior and posterior means and standard deviations. Learning about β could be improved if firm-level data were available. For example, in recent papers by Cahuc, Postel-Vinay, and Robin (2006) and Flinn (2006) firms' profit data were used to identify worker's share of the match surplus.

Figure 3.6 plots the posterior probabilities of being high-skilled conditional on unemployment and employment durations, wages, AFQT scores, IRO and educational attainment of individuals in my sample against their standardized AFQT scores. Different shapes of the markers on Figure 3.6 correspond to the different educational groups of individual. Black cross indicates that an individual has less than 12 years of education, magenta dot indicates that an individual has 12 years of education, blue asterisk indicates that an individual has 13, 14 or 15 years of education, and red plus sign indicates than in individual has 16 or more years of education. The mean posterior probability of being skilled conditional on observables is computed by integration of individual-specific posterior probability of being skilled over the posterior distribution of parameters ω. The posterior conditional probability of being skilled is nearly zero for individuals with standardized AFQT scores below $-.5$ or with less than 12 years of education. For individuals with standardized AFQT scores above -.5 the posterior conditional probability of being skilled varies between zero and one and is increasing in educational attainment. The mean posterior probability of being high-skilled conditional on observables is almost zero for individuals with less than 12 years of education, 0.05 for individuals with 12 years of education, 0.47 for individuals with 13, 14 or 15 years of education and is 0.98 for individuals with 16 or more years of education. Conditional on years of education alone the probability of being high-skilled is 0.0203 for individuals with less than 12 years of education, 0.0547 for individuals with 12 years of education, 0.4640 for individuals with 13, 14 or 15 years of education, and is 0.9685 for individuals with 16 or more years of education. The latter probabilities are computed by integration over the posterior distribution

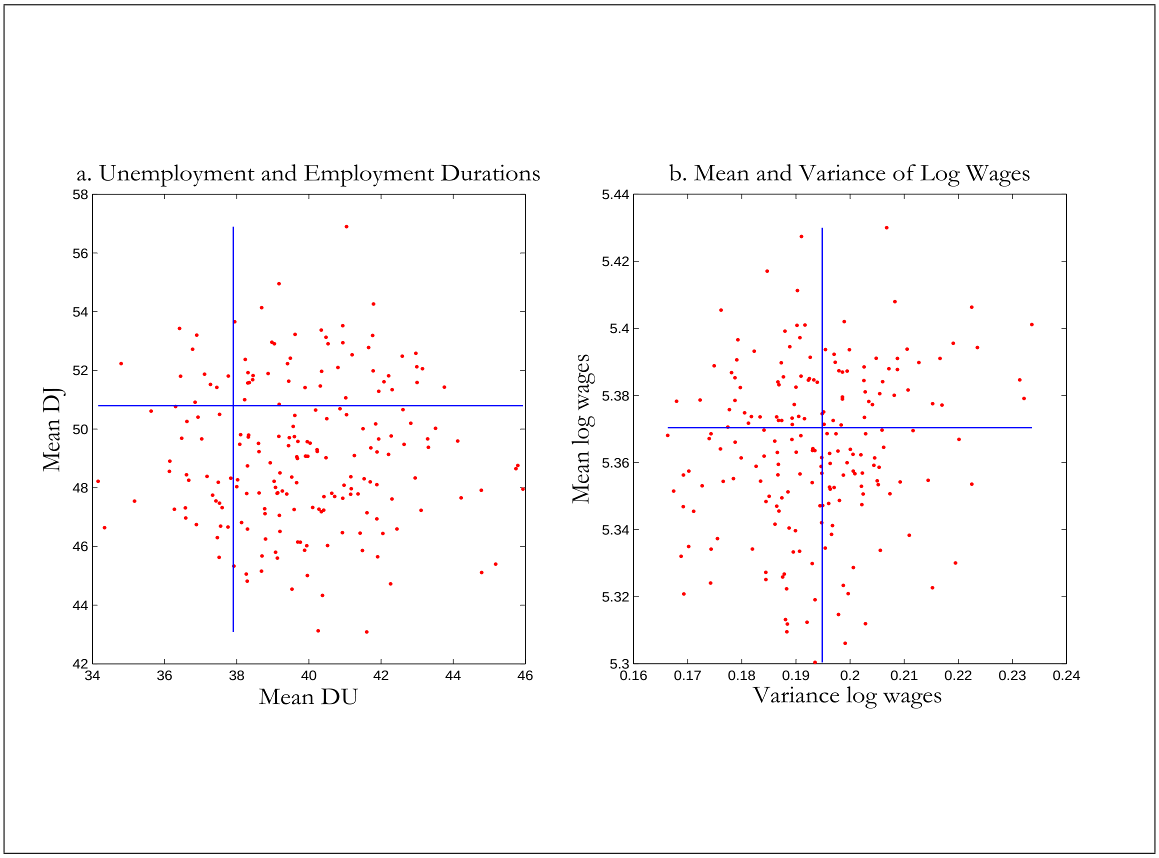
Figure 3.7: Prior and Posterior Distributions of Worker's Surplus Share



of ω of the function $p_{skilled|E} = (1-\mu)\pi_{E,h}/((1-\mu)\pi_{E,h} + \mu\pi_{E,l})$. I will use the latter probabilities in chapter 4 to predict the effects of various labor market policies on labor market outcomes of workers with different educational attainment.

Model fit is examined in Figures 3.8, 3.9 and 3.10 which superimpose selected statistics of the data sample with the joint distributions of these statistics derived from 200 artificial data samples of size 830 (the size of the NLSY79 data sample used in inference) generated conditional on 200 random draws from the joint posterior distribution of parameters. The red dots are the locations of the statistics computed for the artificial data samples and represent the posterior distribution. The point of

Figure 3.8: Posterior Predictive Analysis, Overall Fit



intersection of two straight blue lines indicates the location of these statistics computed for the actual data sample. Figure 3.8 examines how well the model accounts jointly for the mean durations of unemployment and employment and for the mean and variance of the natural log of wages for the entire sample. The model accounts for these statistics well, as the real data sample means of unemployment and job durations, log wages and variance of natural log of wages are located close to the medians of distributions of these statistics across the 200 artificial data samples.

Figures 3.9 and 3.10 show how well the model accounts jointly for means of durations of unemployment and employment, and for the mean and variance of natural log of wages of the four educational groups in the sample. The artificial data samples for figures 3.9 and 3.10 were generated conditional on 200 random draws from the joint posterior distribution of parameters and on the educational attainment and AFQT scores of the individuals in the sample. As can be seen from figure 3.9 the model captures the mean duration of employment reasonably well for the three educational groups except the group with 16 or more years of education. For this group the model underpredicts the mean duration of employment. The model also underpredicts the mean duration of unemployment of the group with less than 12 years of education and overpredicts it for the groups with 12 and between 12 and 16 years of education. The model captures well the mean duration of unemployment for the group with 16 or more years of education.

Figure 3.10 examines how well the model accounts jointly for the mean and variance of log wages of the four educational groups in the sample. The figure indicates

Figure 3.9: Posterior Predictive Analysis, Unemployment and Employment Durations, Conditional on AFQT and EDU

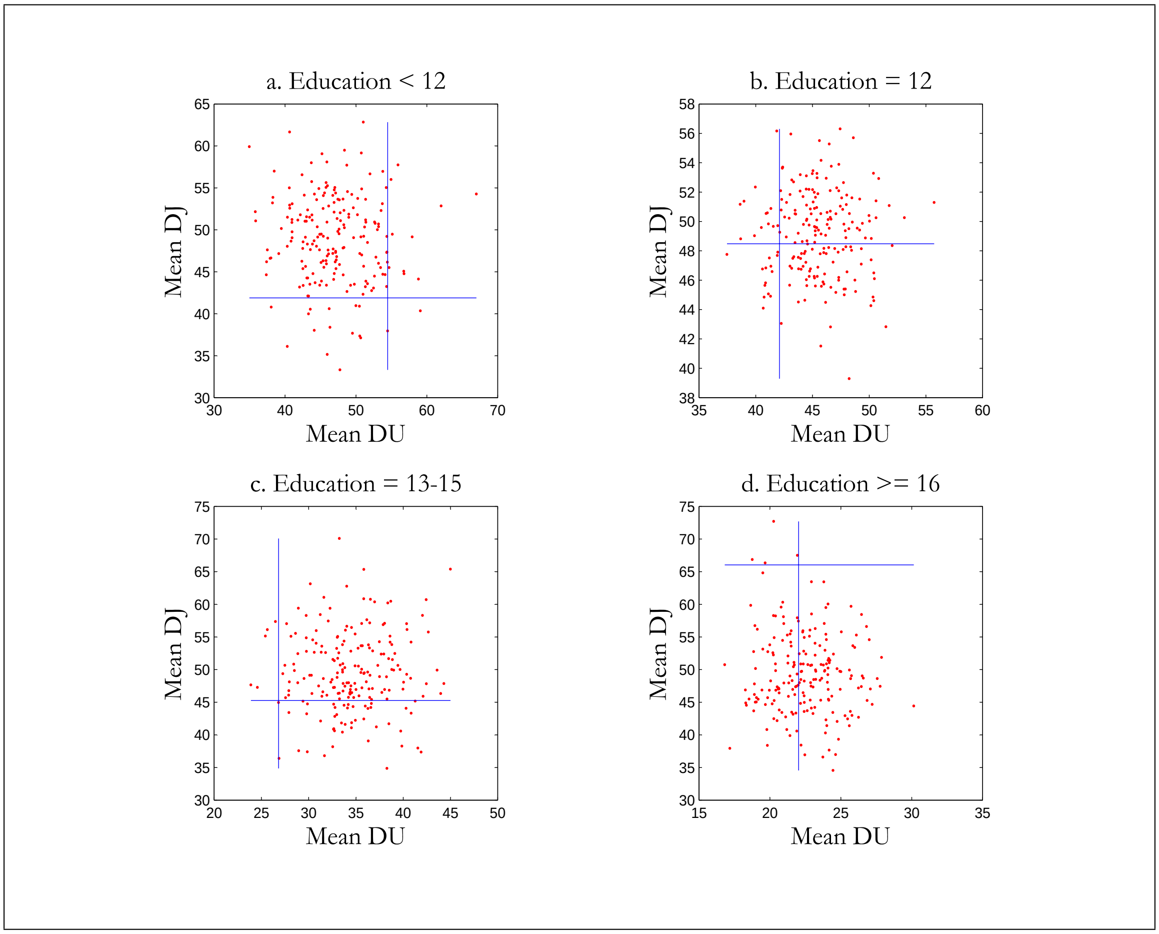
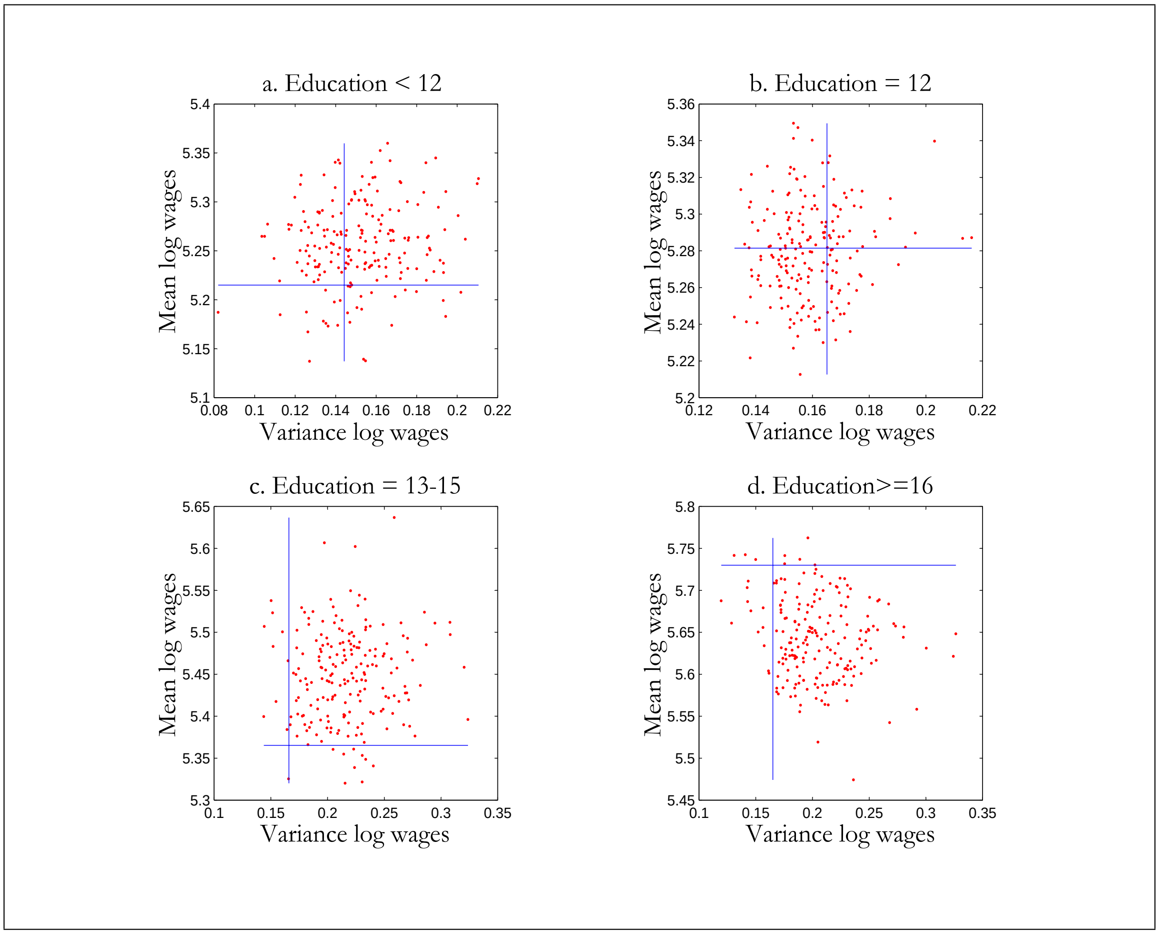


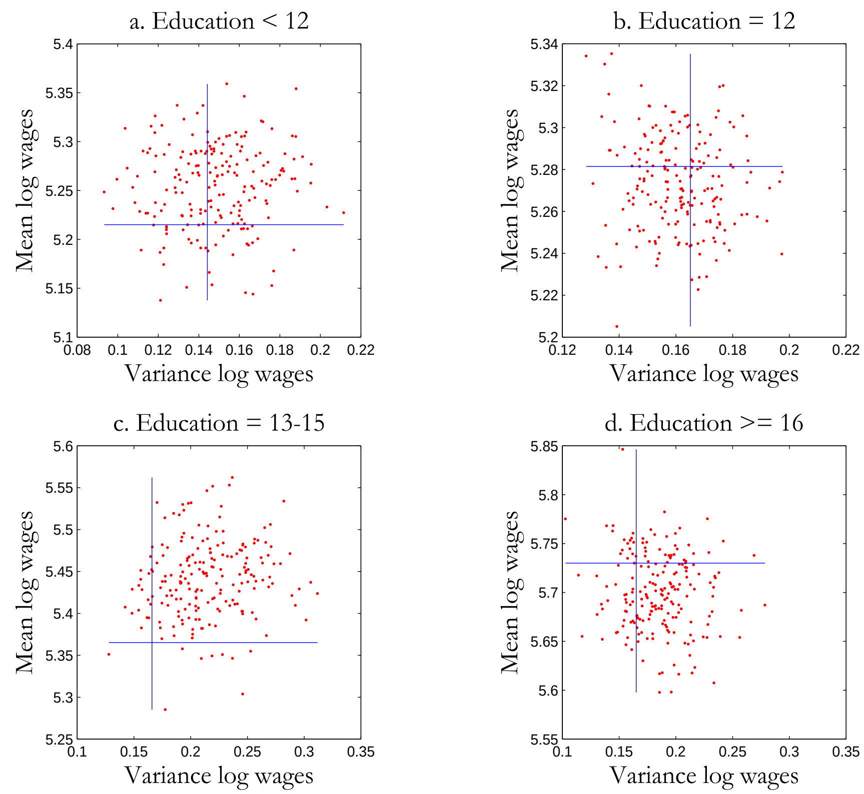
Figure 3.10: Posterior Predictive Analysis, Mean and Variance of Log Wages, Conditional on AFQT and EDU



that model accounts well for mean and variance of log wages for the group with less than 12 years of eduction and of the group with 12 years of education. For the group with years of education between 12 and 16 the model overpredicts mean of log wages and underpredicts the variance, while for the group with 16 or more years of education the model under-predicts mean and over-predicts the variance of log wages.

Figures 3.11 and 3.12 show how well the model accounts jointly for the means of durations of unemployment and employment, and for the mean and variance of natural log of wages of the four educational groups in the sample when the artificial data were generated conditional on 200 random draws from the joint posterior distribution of parameters and on the educational attainment, AFQT scores and the IRO of occupations of the individuals in the sample. Adding IRO to the conditioning set has improved the ability of the model to account for the statistics of durations and wages of the group with 16 or more years of education. This improvement suggests that at the absence of the IRO in the conditioning set the model generates too much mismatch of high-skilled workers, which results in the predicted means of log wages and duration of employment being lower and the predicted variance of log wages being higher than in the data of the group of individuals with 16 or more years of education who have the mean posterior probability of being skilled close to one. The amount of mismatch in the first job is determined by parameter η whose posterior mean is equal to .46. Thus, the model predicts that for about 46% of high-skilled workers their first job will be simple. The distribution of wages of high-skilled workers on simple jobs has a lower posterior mean and a lower mean of posterior precision than

Figure 3.11: Posterior Predictive Analysis, Unemployment and Employment Durations, Conditional on AFQT, IRO and EDU



the distribution of wages of high-skilled workers on complex jobs. Also, the matches between high-skilled workers and simple jobs have lower mean durations than those between high-skilled workers and complex job. If in fact the proportion of mismatch among high-skilled workers employed in their first job is lower than 46%, the model would underestimate the mean duration of employment, underestimate the mean of log wages and overestimate the variance of log wages for high-skilled workers.

Figure 3.12: Posterior Predictive Analysis, Mean and Variance of Log Wages, Conditional on AFQT, IRO and EDU

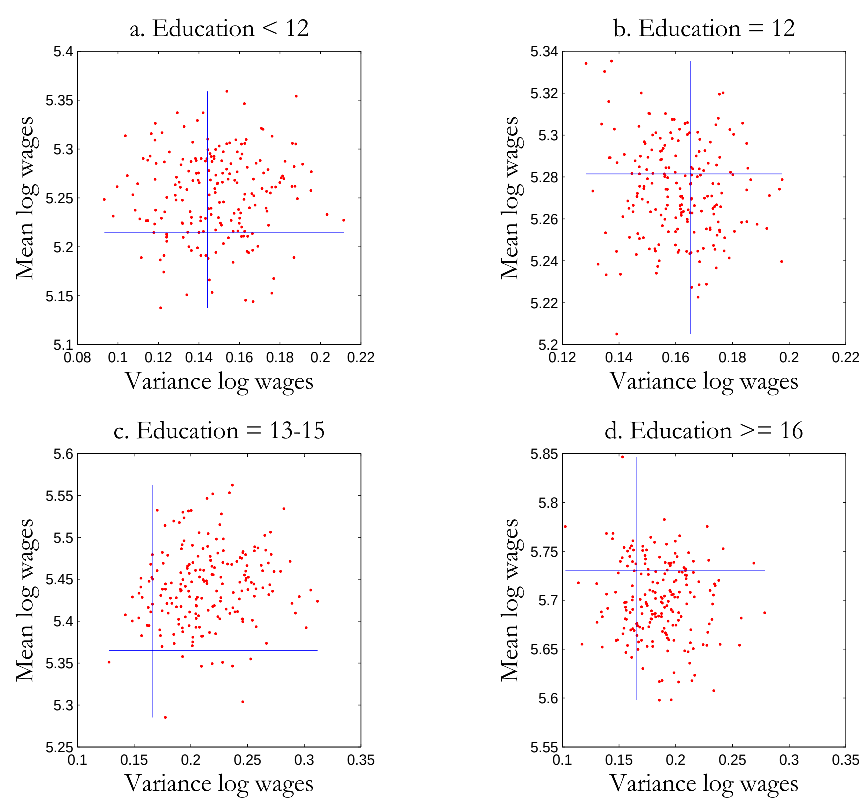


Table 3.3: Prior and Posterior Moments

Param	Prior Mean	Prior Std.	Posterior Mean	Posterior Std.	RNE
b	74.368	68.35	160.465	9.215	0.34
$y_{s,l}$	136.721	167.03	209.472	21.2783	1.58
$y_{s,h}$	210.379	306.46	314.116	62.1972	0.84
$y_{c,h}$	512.995	610.44	382.756	67.1953	1.49
κ	1686604952.57	271163173937.39	79054.997	85940.0032	1.48
ϕ	0.853	0.18	0.842	0.0184	0.27
u	0.243	0.26	0.421	0.0136	0.57
$e_{s,h}$	0.01	0.02	0.032	0.0049	0.24
ψ	0.953	0.06	0.93	0.0105	0.25
δ_s	0.025	0.03	0.02	0.0008	1.12
δ_c	0.012	0.02	0.014	0.0012	0.63
β	0.558	0.21	0.551	0.1981	1.25
η	0.385	0.2	0.464	0.0283	0.27
μ	0.581	0.21	0.727	0.0209	0.29
$\theta q(\theta)$	0.293	0.38	0.046	0.0027	0.26
$w_{s,l}$	115.985	92.94	191.165	3.1597	0.45
$w_{s,h}$	152.168	114.54	247.411	15.8878	1.05
$w_{c,h}$	447.98	423.42	323.422	11.6735	0.31
x_l	-0.684	0.91	-0.387	0.0391	0.31
x_h	1.189	0.91	0.948	0.0401	0.39
y_s	-0.682	0.91	-0.654	0.0297	0.44
y_c	1.188	0.91	1.204	0.0528	0.33
$h_{w,1}$	20.045	20.06	6.813	0.441	0.46
$h_{w,2}$	20.086	19.9	4.592	1.028	0.35
$h_{w,3}$	20.159	20.21	7.185	0.9558	0.75
$h_{afqt,l}$	1.327	1.34	1.438	0.0866	0.89
$h_{afqt,h}$	1.333	1.33	4.264	0.5172	0.79
$h_{f1,s}$	0.994	1	2.14	0.137	0.41
$h_{f1,c}$	1.007	1.01	4.204	0.6302	0.48
π_{l1}	0.25	0.14	0.16	0.0151	0.93
π_{l2}	0.25	0.14	0.75	0.0188	1.57
π_{l3}	0.252	0.15	0.082	0.0131	2.14
π_{l4}	0.249	0.14	0.008	0.0048	0.53
π_{h1}	0.251	0.15	0.009	0.0061	1.37
π_{h2}	0.249	0.14	0.115	0.0365	0.16
π_{h3}	0.25	0.14	0.188	0.0301	1.62
π_{h4}	0.249	0.14	0.689	0.0441	0.2

CHAPTER 4

POLICY EXPERIMENTS

This chapter presents results from the following counterfactual experiments:

1. Employment subsidy of \$28 per week for employing low-skilled workers ($a_h = 28$), which is equal to 15% of the posterior mean of the wage of low-skilled workers on simple jobs $w_{s,l}$;

2. One-time hiring subsidy of \$1400 for hiring low-skilled workers ($H_l = 1400$), which is equal to 733% of the posterior mean of the wage of low-skilled workers on simple jobs $w_{s,l}$;

3. Employment subsidy of \$65 for employing workers on complex jobs ($a_h = 65, y_{s,h} - 65$), which is equal to 17% of the posterior mean of the wage of high-skilled workers on complex jobs $w_{c,h}$;

4. Employment subsidy of \$64.4 for employing high-skilled workers ($a_h = 64.4$);

5. One-time hiring subsidy of \$3400 for hiring a high-skilled worker ($H_h = 3400$), which is equal to 1100% of the posterior mean of the mean wage of high-skilled workers;

6. Employment subsidy of \$28 for employing low-skilled workers financed by a lump-sum tax on employed high-skilled workers ($a_l = 28, a_h = -62.5$);

7. Increase in the proportion of high-skilled workers $1-\mu$ by .10 to model the effect of the policy which increases skill level of workers;

8. Increase in the proportion of high-skilled workers $1-\mu$ by .10 introduced simultaneously with employment subsidy for employing low-skilled workers financed by a lump-sum tax on employed high-skilled workers ($a_l = 5$, $a_h = -5.2$);

9. Increase in unemployment income b by \$15 to model the effect of a lump-sum increase in the level of unemployment benefits. The change in unemployment income for this policy experiment is equal to 9% of the posterior mean of unemployment income b.

The size of the subsidies in 1.-5. is chosen so that the expected costs of these five policies were approximately equal. The policy experiments in 1.-9. amount to adding a fixed quantity to an unknown parameter in each case. Uncertainty about all of the parameters translates into uncertainty about the quantitative predictions of the model with regard to the impacts of the policies on endogenous variables of interest. I evaluate the equilibrium effects of the policies for a range of values of parameters which is representative of their posterior distribution, which allows me to asses the uncertainty about the equilibrium outcomes.

Table 4.1 lists some endogenous variables whose response to policies may be of interest to policymakers. Two of these variables are the weekly per-capita costs of a policy Def and the total expected welfare $Welf$.

The weekly per-capita cost of a policy or of a combination of policies (Def) in the next to last row of Table 4.1 is computed as

$$\begin{aligned} Def &= a_l e_{s,l} + a_h(e_{s,h} + e_{c,h}) + H_h\theta q(\theta)(1-\phi)u + H_h\theta q(\theta)(1-\eta)e_{s,h} \\ &+ H_l\eta\theta q(\theta)\phi u - F_h(e_{s,h}\delta_s + e_{c,h}\delta_c) - F_l e_{s,l}\delta_s. \end{aligned} \tag{4.1}$$

For example, the weekly per-capita cost of employment subsidy for employing a low-skilled worker will be computed using equation (4.1) as $a_l \cdot e_{s,l}$. The weekly per-capita cost of this policy is computed as the amount of the subsidy a_l multiplied by the proportion of the labor force to whom the subsidy will be applied $e_{s,l}$. Similarly, the weekly per capita cost of a one-time subsidy for hiring a low-skilled worker will be computed as $H_l \cdot \eta\theta q(\theta)\phi u$. The weekly per-capita cost of a hiring subsidy is computed as the amount of the subsidy H_l multiplied by the proportion of the labor force to whom the subsidy will be applied $\eta\theta q(\theta)\phi u$. The latter expression is a steady-state proportion of unemployed low-skilled workers who exit unemployment after meeting a simple vacancy. In general, the weekly per-capita cost of a policy or of a combination of policies in expression (4.1) is computed as a summation of costs of policies multiplied by the proportions of the labor force to whom these policies are applied. For the policy which increases unemployment income b by \$15 per week the weekly per-capita cost is computed as $15 \cdot u_{post.}$ where $u_{post.}$ is used to denote the overall unemployment rate after putting the policy in place.

The total expected welfare in the last row of Table 4.1 is a Benthamite social welfare function, computed as

$$\begin{aligned} Welf &= \phi u \cdot U_l + (1-\phi)u \cdot U_h + e_{s,l} \cdot (W_{s,l} + J_{s,l} + H_l) \\ &+ e_{s,h} \cdot (W_{s,h} + J_{s,h} + H_h) + e_{c,h} \cdot (W_{c,h} + J_{c,h} + H_h). \end{aligned} \quad (4.2)$$

The total expected welfare is computed as the sum of the expected streams of incomes that different groups of participants of the labor market receive in the cross-skill matching equilibrium, multiplied by the sizes of these groups. In particular, the sum in (4.2) includes the following components: the expected stream of income of unemployed low-skilled workers U_l multiplied by the proportion of such workers in the labor force ϕu; the expected discounted stream of income of unemployed high-skilled workers U_h multiplied by the proportion of such workers in the labor force $(1-\phi)u$; the expected discounted streams of incomes of employed workers $W_{s,l}$, $W_{s,h}$ and $W_{c,h}$ multiplied by the respective proportions of these groups of workers in the labor force $e_{s,l}$, $e_{s,h}$ and $e_{c,h}$; the expected discounted streams of income of firms with filled vacancies $J_{s,l}+H_l$, $J_{s,h}+H_h$ and $J_{c,h}+H_h$ multiplied by respective sizes of these sets of firms $e_{s,l}$, $e_{s,h}$ and $e_{c,h}$. The expected discounted streams of income of firms with vacant jobs V_s and V_c do not appear in the definition (4.2) because they are equal to zero in the steady-state equilibrium. A similar approach to the evaluation of the welfare impact of a policy within the context of a search and matching model has been taken by Flinn (2006).

Sections 4.1-4.9 discuss the effects of policies on the functions of interest in table 4.1 in detail. Tables 4.2-4.10 in sections 4.1-4.9 show the effects of the policies on the distributions of functions of interest from Table 4.1. The $Pre.M.$ and $Pre.S.$ columns of Tables 4.2-4.10 contain the before-policy posterior means and standard deviations of functions of interest respectively. The $Post.M.$ and $Post.S.$ columns of Tables 4.2-4.10 contain the predicted after-policy means and standard deviations of functions of interest respectively. The $Mean\Delta$ and $Std.\Delta$ columns contain means and standard deviations of predicted differences between before- and after-policy outcomes respectively. The $Mean\%\Delta$ column contains the mean of the percentage change in an outcome, and $P_{incr.}$ column presents the posterior probability that a policy will produce an increase in a function of interest. The values in the last eight columns of Tables 4.2-4.10 are computed using the following steps:

1. Randomly choose M[1] draws from the joint posterior distribution of the structural parameters $\beta, \mu, \kappa, b, y_{s,l}, y_{s,h}, y_{c,h}, \delta_s, \delta_c$

2. Reweigh the draws obtained in step 1 so that they satisfy the necessary conditions for the existence of the cross-skill matching equilibrium after a policy has been put in place, which includes the conditions for nonnegativity of match surpluses $S_{s,l}$, $S_{s,h}$ and $S_{c,h}$ as well as the necessary condition for the firm entry into the complex sector as stated in (2.35). It is possible that after putting a policy in place the resulting combination of parameters will fail to satisfy one or more of these four conditions. For instance, in the case of increase in unemployment income adding 15 to $b^{(n)}$ for some n might result in violation of the assumption

[1] I chose $M = 400$ so that the resulting draws were representative of the posterior distribution and at the same time did not impose large burden in terms of the time required to compute the model equilibrium.

on the production technology which requires that $max\{y_{s,l}, y_{s,h}\} > b$, in which case the vector $\beta^{(n)}, \mu^{(n)}, \kappa^{(n)}, b^{(n)}_{post.}, y^{(n)}_{s,l}, y^{(n)}_{s,h}, y^{(n)}_{c,h}, \delta^{(n)}_s, \delta^{(n)}_c$ will result in one or both match surpluses $S_{s,l}$ and $S_{s,h}$ being negative, which will be inconsistent with the existence of a cross-skill matching equilibrium for this parameter configuration. If a particular draw of parameters turns out to be inconsistent with the existence of the cross-skill matching equilibrium after the policy is put is place, I omit such a draw from the analysis. This procedure is equivalent to changing the prior distribution of parameters defined in (3.20) so that they are consistent with the existence of the equilibrium *before and after* the policy has been put in place. In particular, the procedure is equivalent to redefining the subset of parameters $\mathbf{S}$ in (3.20) by further restricting $\mathbf{S}$ to include only parameter combinations which produce nonnegative match surpluses $S_{s,l}$, $S_{s,h}$, $S_{c,h}$ and satisfy the necessary condition for firm entry into the complex sector (2.35) *after* the policy has been put in place. The probability that the parameters will produce a cross-skill matching equilibrium after the policy change, given the original prior on parameters as defined in (3.20), is .83 in case of the policies in items 1 and 2, is 1 in case of the policies in items 3 and 4, is .92 in case of the policy in item 5, is .73 in case of the policy in item 6, is 1 in the case of the policies in items 7 and 8, and is .98 in case of the policy in item 9.

3. For every draw obtained in step 2 solve the system of equations (2.10), (2.11), (2.12), (2.28) and (2.29) with the policy measures put in place to find the after-policy vector of equilibrium quantities $[\theta^{(n)}_{post.}, \eta^{(n)}_{post.}, \phi^{(n)}_{post.}, u^{(n)}_{post.}, e^{(n)}_{s,hpost}]$,$n =$

$1, ..., M$. Use this vector to compute functions of interest from Table 4.1 for each n.

4. Using the post-policy distributions of functions of interest obtained in step 3 compute corresponding statistics to fill columns $Post.M.$, $Post.S.$, $Mean.\Delta$, $Std.\Delta$, $Mean\%\Delta$ and $P_{incr.}$. The column $P_{incr.}$ contains proportion of vectors of structural parameters obtained in step 3 for which a function of interest is increased by a policy.

4.1 Subsidy for Employing a Low-skilled Worker

The effect of the employment subsidy of \$28 per week given to a firm for employing a low-skilled worker is shown in Table 4.2. The probability that the cross-skill matching equilibrium will exist after this policy change, given the original prior on parameters as defined in (3.20), is .83. Thus, 17% of the draws from the posterior distribution of the parameters will fail to generate the cross-skill matching equilibrium after the policy has been put in place. The condition which fails in these 17% of the draws is the necessary condition for firm entry into the complex sector (2.35).

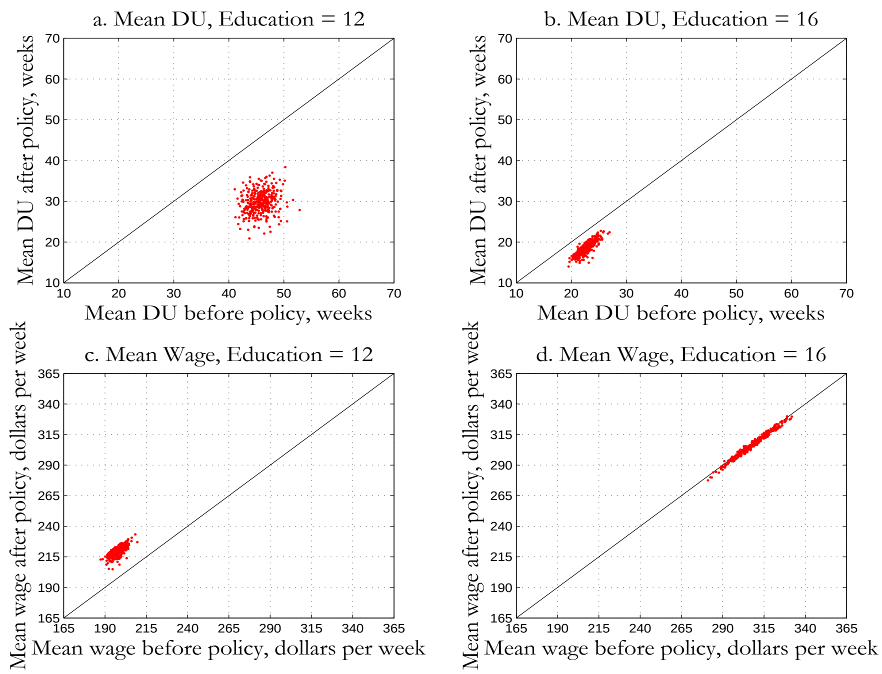
The policy increases labor market tightness θ, thus increasing the job arrival rate $\theta q(\theta)$. The share of simple vacancies in the mass of vacancies η also increases. Together the increases in θ and η increase the weekly exit rate from unemployment of low-skilled workers by 56% on average. These changes imply a decrease in the mean unemployment duration for low- and high-skilled workers. Total unemployment u decreases, as well as the number of low- and high-skilled unemployed u_l and u_h.

The posterior mean of the number of mismatched high-skilled workers $e_{s,h}$ increases, because the subsidy stimulates firm entry in the simple sector and generates firm exit from the complex sector - the number of jobs in the simple sector NF_s increases and the number of jobs in the complex sector decreases.

The wages of low-skilled workers on simple jobs $w_{s,l}$ increase, as the subsidy is divided between workers and firms in the process of wage bargaining. On average low-skilled workers receive about 82% of the subsidy. Wages paid to high-skilled workers on simple jobs $w_{s,h}$ and on complex jobs $w_{c,h}$ also increase because job creation in the simple sector improves outside option of high-skilled workers thus strengthening their position in the wage bargaining with firms. The policy is beneficial for both high- and for low-skilled workers because the present discounted streams of income from unemployment and employment increase for both types of workers. The weekly per capita output Y increases by $18 on average, the amount high enough to cover the mean expected per-period cost of the policy equal to $13 per week.

Figure 4.1 present some of the effects of the policy on selected labor market outcomes of workers with 12 years of education and of workers with 16 or more years of education. These two groups are the two most numerous educational groups in my sample. To obtain the effects of the policy for a particular educational group I weight the predicted labor market outcomes of low- and high-skilled workers by the educational-group-specific posterior probability of being skilled as computed in section 3.4. Figure 4.1 is visually informative about the uncertainty in the predicted equilibrium impacts. The horizontal axes of the plots of figure 4.1 measure the values

Figure 4.1: Before- and After-policy Unemployment Durations and Wages, Employment Subsidy for Employing a Low-Skilled Worker



of endogenous variables before the policy, and the vertical axes measure the values of these variables after the policy was implemented. The graphs suggest that there is more uncertainty about the policy effect on the mean unemployment duration and unemployment rate of workers with 12 years of education than of those with 16 years of education, and that the uncertainty about the level effects of the policy on wages is low compared to the uncertainty about the before-policy level of wages of the workers of the two educational groups.

4.2 Subsidy for Hiring a Low-Skilled Worker

The effect of a one-time hiring subsidy of \$1400 given to a firm for hiring a low-skilled worker is shown in Table 4.3. The amount of the hiring subsidy is chosen so that the expected outlays on the subsidy are approximately equal to those of an employment subsidy of \$28 given to firms per period for employing a low-skilled worker. The probability that the cross-skill matching equilibrium will exist after this policy change, given the original prior on parameters as defined in (3.20), is .83. Thus, 17% of the draws from the posterior distribution of the parameters will fail to generate the cross-skill matching equilibrium after the policy has been put in place. The condition which fails in these 17% of the draws is the necessary condition for firm entry into the complex sector (2.35).

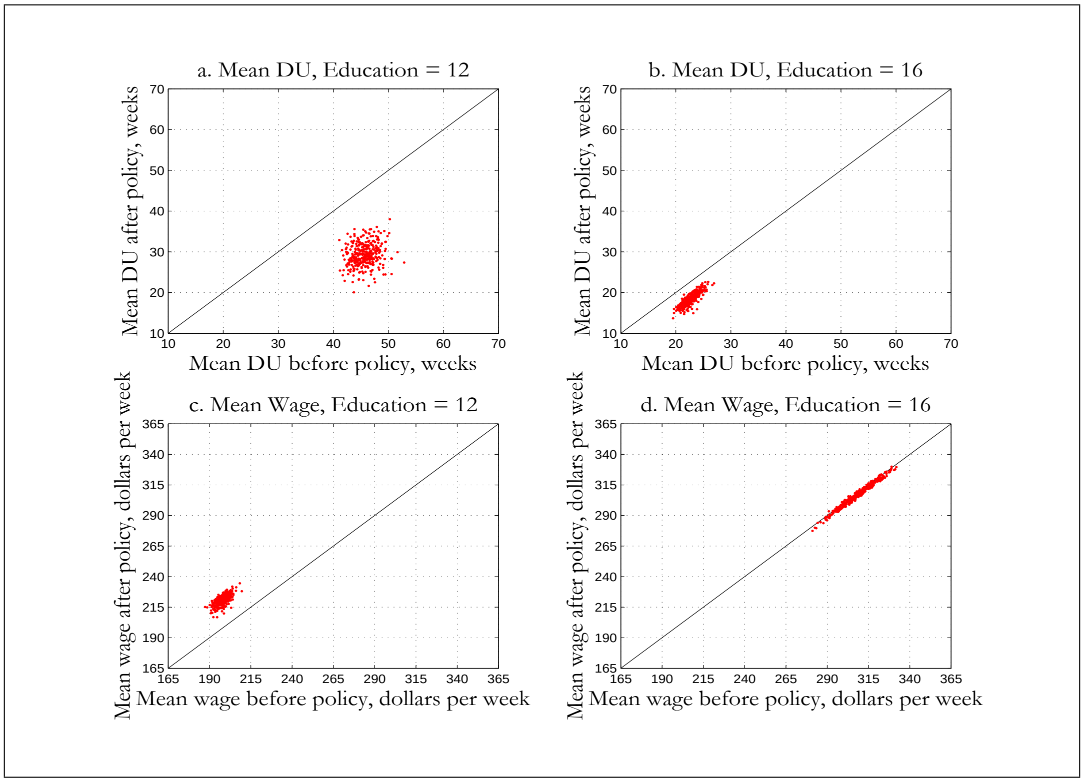
The effect of the hiring subsidy of \$1400 is very similar to that of the employment subsidy of \$28 which has been analyzed in section 4.1. The posterior means of the predicted policy impacts on the functions of interest to a policymaker in table 4.3 are very similar to those in the table 4.2. The posterior standard deviations of the effects of the policy tend to be larger for the hiring subsidy compared to the employment subsidy. This can be rationalized as follows. In the case of the employment subsidy a fixed constant 28 is added to each of the M draws from the posterior distribution of $y_{s,l}$ and the model is solved M times for the new after-policy equilibrium as discussed in the introduction to this chapter. In the case of the hiring subsidy an amount $1400 \cdot \delta_s$ is added to each of the M draws from the posterior distribution of $y_{s,l}$ and the model is solved M times for the new after-policy equilibrium. Thus, the variance of the after-policy per-period return from a simple job filled with a low skilled worker $y_{s,l} + 1400 \cdot \delta_s$ in the case of the hiring subsidy is higher than the after-policy per-period return from the same match $y_{s,l} + 28$ in the case on the employment subsidy if $y_{s,l}$ and δ_s are not correlated, as is the case for the 400 draws from the posterior I am using for the policy analysis. Higher variance of the per-period return from the match between a low-skilled worker and a simple job in the case of a hiring subsidy compared to the employment subsidy translates into the higher variance of the predicted policy impacts on the variables of interest to a policymaker. Thus, a risk-averse policymaker would prefer the employment subsidy to the hiring subsidy because both policies produce the same mean effects but the employment subsidy produces lower variance.

Figure 4.2 present some of the effects of the policy on selected labor market outcomes of workers with 12 years of education and of workers with 16 or more years of education. The figure is very similar to Figure 4.1 which presents the impacts of the employment subsidy of $28 for employing a low-skilled worker on labor market outcomes of the two educational groups of workers.

4.3 Employment Subsidy for a Complex Job

The effect of the employment subsidy of $65 for complex jobs is presented in Table 4.4. The subsidy of 65$ is chosen so that the expected total cost of the policy is comparable to the expected total cost of the introduction of the employment subsidy of $28 for employing low-skilled workers. The subsidy is modeled by introducing the

Figure 4.2: Before- and After-policy Unemployment Durations and Wages, Hiring Subsidy for Hiring a Low-skilled Worker



employment subsidy a_h of \$65 and by subtracting \$65 from $y_{s,h}$ at the same time to make the subsidy apply to complex jobs only. The probability that the cross-skill matching equilibrium will exist after this policy change, given the original prior on parameters as defined in (3.20), is 1.

The subsidy for complex jobs increases the job arrival rate $\theta q(\theta)$ and decreases the share of simple vacancies η. The net effect of these changes is the decrease in the exit rate of low-skilled workers from unemployment $\eta\theta q(\theta)$. The policy produces an increase in the mean duration of unemployment of low-skilled workers by 10 weeks on average and almost no change in the unemployment duration of high-skilled workers.

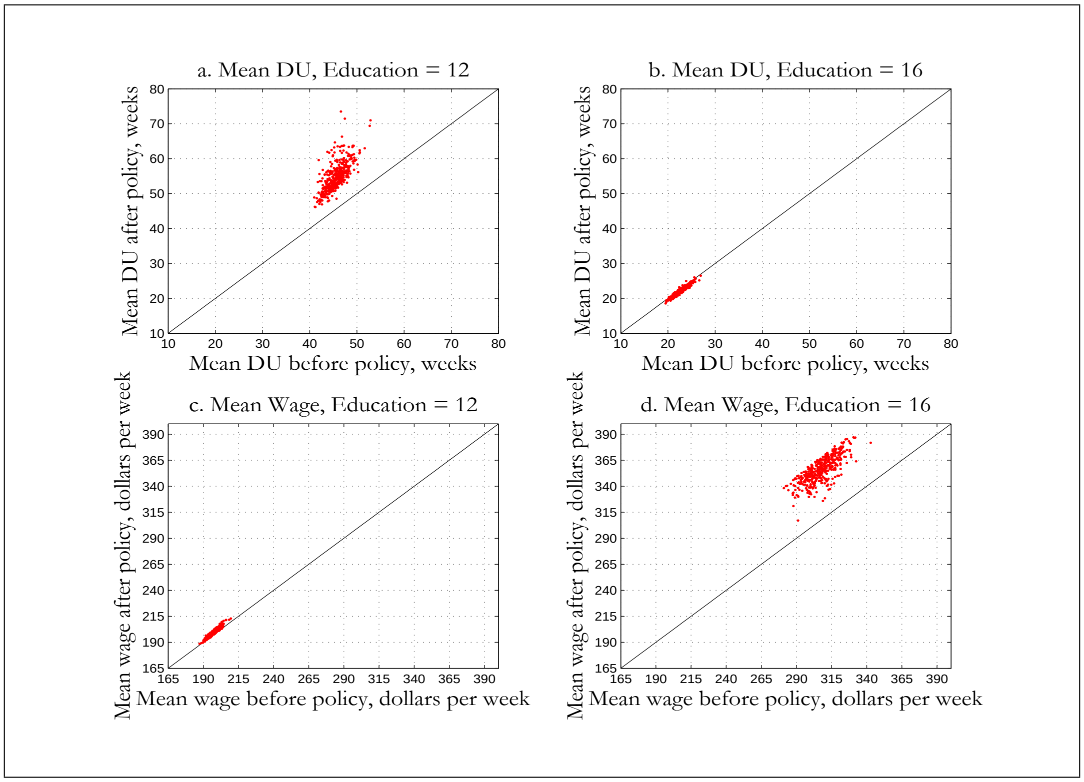
The number of unemployed low-skilled workers u_l increases. Because job destruction rate of simple jobs is not changed by the policy, the increase in the low-skilled unemployment is caused by the decrease in the rate of exit of low-skilled workers from unemployment. The policy decreases amount of vacancies in the simple sector because with increased vacancy supply in the complex sector the skill distribution of unemployed job seekers changes so that the proportion of low-skilled workers in the mass of unemployed increases. This makes creating simple vacancies less attractive to a firm because now simple vacancy has higher chances to meet unemployed low-skilled worker who has lower productivity on simple job than a high-skilled worker.

The policy increases total unemployment, with low-skilled unemployment increasing by 10% on average and high-skilled unemployment decreasing by 5% on average. The duration of unemployment and the unemployment rate of high-skilled workers decreases only slightly. The reason for the insufficient entry of complex vacancies is that most of the subsidy (85%) is appropriated by high-skilled workers through the wage bargaining with firms. The expected change in the weekly per capita output Y is -4.5% with zero probability of an increase.

Figure 4.3 presents some of the policy effects in a way which is visually informative about the uncertainty about the equilibrium outcomes. The figures suggest that, as in the case of skill upgrading and employment subsidies for simple jobs, there is more uncertainty about the policy effect on the mean unemployment duration of workers with 12 years of education than those of workers with 16 or more years of education. The figure suggests that the posterior distribution of the change in the mean duration of unemployment of workers with 16 or more years of education is tightly centered around zero. The impact of the policy on wages of workers with twelve years of education is also close to zero. The figure suggests a strong positive effect of the policy on the mean wages of workers with 16 and more years of education, which is bounded from above by the amount of the subsidy.

Thus, the model suggests that the employment subsidies for complex jobs introduced as a mean of reduction of job competition between low- and high-skilled workers is unlikely to reduce unemployment among the low-skilled. On the contrary, the results suggest that by participating in the simple sector unemployed high-skilled workers induce a positive externality on low-skilled workers because of high productivity of high-skilled workers on simple jobs. The employment subsidy for complex jobs reduces the number of high-skilled workers in the pool of unemployed, thus decreasing expected returns from simple jobs to firms. The subsequent exit of simple

Figure 4.3: Before- and After-policy Unemployment Durations and Wages, Employment Subsidy for a Complex Job



vacancies from the market adversely affects unemployment rate and mean duration of unemployment of low-skilled workers. Also, the employment subsidy for complex jobs does not seem to be effective if the goal of a policymaker is to stimulate job creation in the high-tech (complex) sector of the economy. The subsidy increases overall employment in the complex sector by 7% only.

4.4 Subsidy for Employing a High-skilled Worker

The effect of the employment subsidy of \$64.4 for employing a high-skilled worker is presented in Table 4.5. The subsidy $a_h = 64.4\$$ is chosen so that the expected total cost of the policy is comparable to the expected total cost of the introduction of the employment subsidy of \$28 for low-skilled workers studied in section 4.1 or introduction of employment subsidy for complex jobs studied in section 4.3. The probability that the cross-skill matching equilibrium will exist after this policy change, given the original prior on parameters as defined in (3.20) is 1.

The results suggest that when the goal of a policymaker is to stimulate job creation in the high-tech (complex) sector of the economy without undermining labor market position of low-skilled workers, the employment subsidy for keeping high-skilled workers on the payroll is a more effective policy that the employment subsidy for complex jobs. The subsidy for employing high-skilled workers increases the job arrival rate $\theta q(\theta)$ and decreases the share of simple vacancies η by 10% on average. The net effect of these changes is no change in the exit rate of low-skilled workers from unemployment $\eta\theta q(\theta)$ on average. Therefore, the mean duration on unemployment of low-skilled workers as well as the overall unemployment rate does not change. The number of high-skilled workers employed in complex jobs $e_{c,h}$ increases by 6% on average. This effect is similar to the effect on $e_{c,h}$ of the employment subsidy for complex jobs in section 4.3, but the policy does not have adverse effects on labor market outcomes of low-skilled workers.

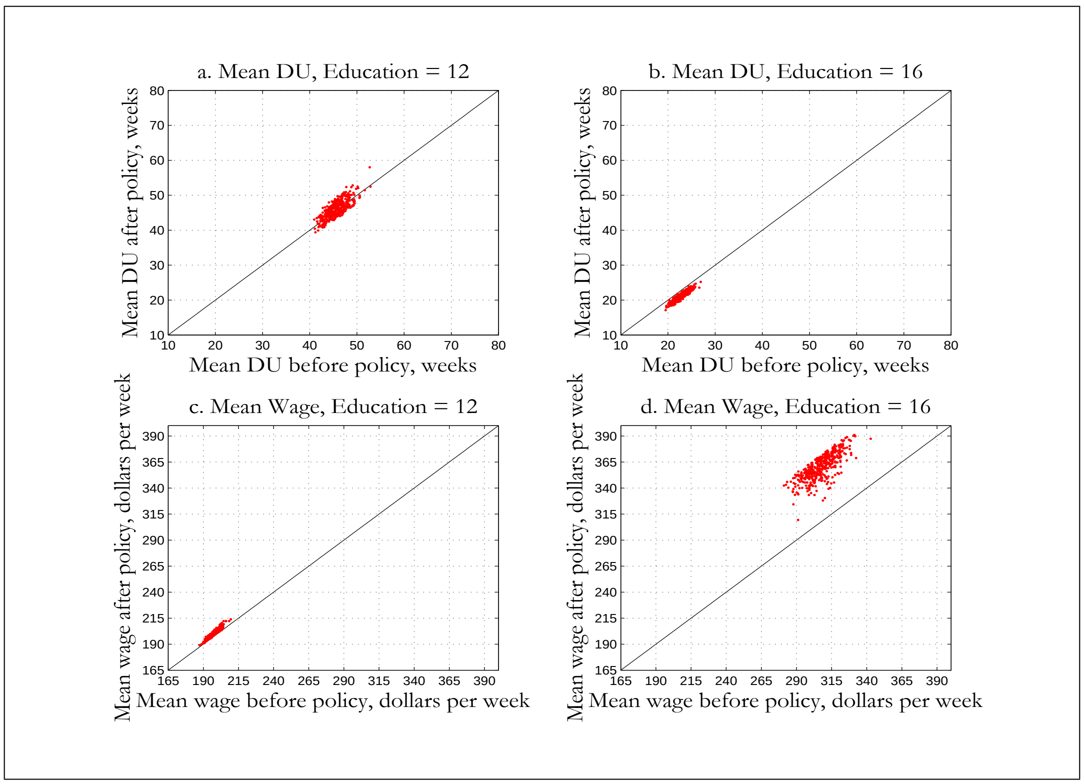
The policy is beneficial for high-skilled workers and has almost no effect on the expected streams of income of unemployed and employed low-skilled workers. Therefore, the aggregate welfare will increase as a result of this policy.

Figure 4.4 present some of the policy effects in a way which is visually informative about the uncertainty about the equilibrium outcomes. The figures suggest that there is more uncertainty about the level effect of the policy on the mean unemployment duration of workers with 12 years of education than those of workers with 16 or more years of education. The impact of the policy on wages of workers with twelve years of education is also close to zero. The figure suggests a strong positive effect of the policy on the mean wages of workers with 16 and more years of education, which is bounded from above by the amount of the subsidy.

4.5 Subsidy for Hiring a High-skilled Worker

The effect of a one-time hiring subsidy of \$3400 for hiring a high-skilled worker is presented in Table 4.6. The subsidy $H_h = 3400$ is chosen so that the expected total cost of the policy is comparable to the expected total cost of the introduction of the employment subsidy of \$28 for simple jobs studied in section 4.1 or introduction of

Figure 4.4: Before- and After-Policy Unemployment Durations and Wages, Employment Subsidy for Employing a High-Skilled Worker



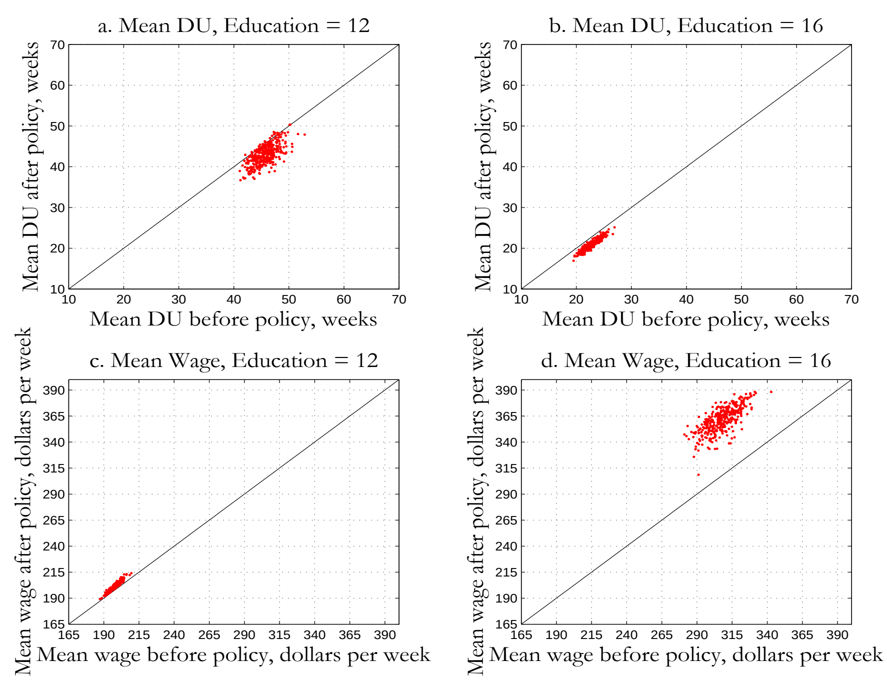
employment subsidy for complex jobs studied in section 4.3. The probability that the cross-skill matching equilibrium will exist after this policy change, given the original prior on parameters as defined in (3.20) is .92. Thus, 8% of the draws from the posterior distribution of the parameters will fail to generate the cross-skill matching equilibrium after the policy has been put in place. The condition which fails in these 8% of the draws is the necessary condition for firm entry into the complex sector (2.35).

The results suggest that when the goal of a policymaker is to stimulate job creation in the high-tech (complex) sector of the economy without undermining labor market position of low-skilled workers, the hiring subsidy for hiring high-skilled workers discussed in this section is also a more effective policy than the employment subsidy for complex jobs discussed in section 4.3 and might even be more effective than the employment subsidy for employing high-skilled workers discussed in section 4.4, because it may have a potential to generate the same increase in the number of complex jobs $e_{c,h}$ and improve labor market outcomes of low-skilled workers at the same time. However, some further analysis is needed to demonstrate that the hiring subsidy H_h can generate the same increase in $e_{c,h}$ as the employment subsidy a_h of the comparable cost, and to improve labor market outcomes of low-skilled workers at the same time. In particular, to make the policy in this section comparable to policy in section 4.4 the expected costs of the two policies need to be made equal, and this requires further experimentation with the amount of subsidy for hiring a high-skilled worker. The expected cost of the one-time hiring subsidy of \$3400 is about \$10.5 per week and on average the one-time hiring subsidy of \$3400 generates a 4% increase in the number of complex jobs $e_{c,h}$, while the expected cost of the weekly employment subsidy of \$64.4 studied in section 4.4 is about \$13.6 per week and the average increase in the number of complex jobs $e_{c,h}$ associated with the introduction of this subsidy is about 6%. Whether it is possible to increase the amount of complex jobs $e_{c,h}$ to 6% and keep the expected cost close to \$13.6 at the same by a carefully chosen size of the hiring subsidy H_h needs further investigation.

The hiring subsidy of \$3400 given to a firm for hiring a high-skilled worker increases the job arrival rate $\theta q(\theta)$ and decreases the share of simple vacancies η. The net effect of these changes is an increase in the exit rate of low-skilled workers from unemployment $\eta\theta q(\theta)$. Therefore, the mean durations of unemployment of low-skilled and high-skilled workers both decrease. The policy is beneficial for high- and low-skilled workers in that it decrease mean durations of unemployment of the two groups and increases wages of high-skilled workers.

Figure 4.5 present some of the policy effects in a way which is visually informative about the uncertainty about the equilibrium outcomes. The figure suggests that the probability that the mean unemployment duration of workers with 12 years of education will decrease is close to one, and that the probability that the mean wages of this group will increase is also close to one.

Figure 4.5: Before- and After-policy Unemployment Durations and Wages, Hiring Subsidy for Hiring a High-skilled Worker



4.6 Subsidy for Employing a Low-skilled Worker Financed by a Tax on High-skilled Workers

The analysis in the previous sections has focused on comparing effects of policies with approximately equal expected outlays by changing one policy instrument at a time. This section presents effects of a policy mix with balanced government budget. As have been shown in sections 4.1 and 4.3, simple vacancy supply is more sensitive to employment subsidy than complex vacancy supply. This makes it possible to decrease low-skilled unemployment by introducing the employment subsidy financed entirely by a lump-sum tax on employed high-skilled workers without affecting employment of high-skilled workers substantially. The effects of the employment subsidy of \$28 for employing a low-skilled worker financed by a lump-sum tax of \$62.5 on employed high-skilled workers is presented in Table 4.7.

The probability that the cross-skill matching equilibrium will exist after this policy change, given the original prior on parameters as defined in (3.20), is .73. Thus, 23% of the draws from the posterior distribution of the parameters will fail to generate the cross-skill matching equilibrium after the policy has been put in place. The condition which fails in these 23% of the draws is the necessary condition for firm entry into the complex sector (2.35).

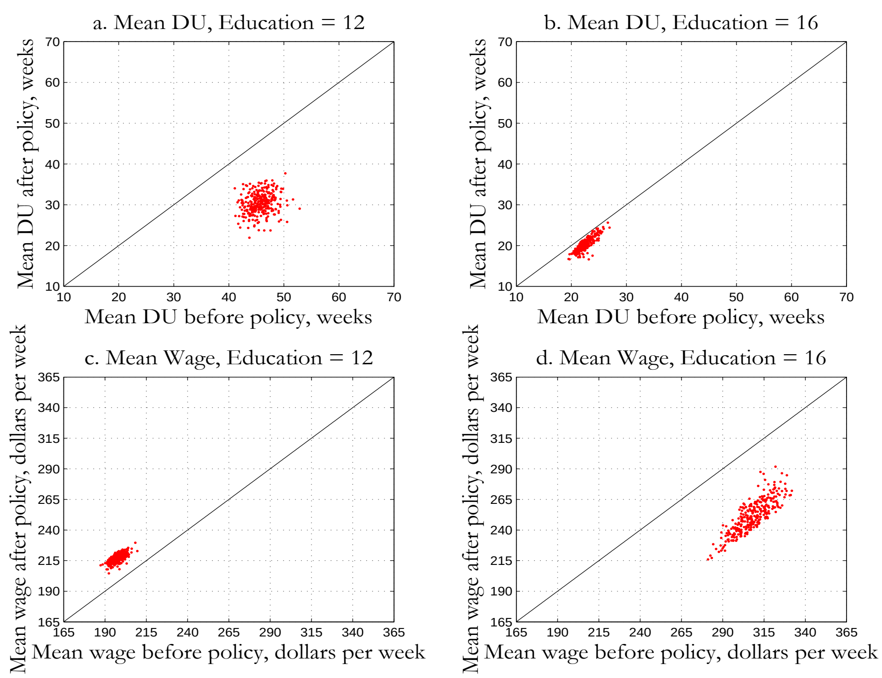
The expected cost of this policy is close to zero. In fact, the policy generates some government surplus. It is possible to balance government budged completely by choosing a lower lump-sum tax on employed high-skilled workers. The policy produces a decrease of overall unemployment rate u with probability one. The number of low-skilled unemployed u_l and the number of high-skilled unemployed u_h both decrease on average, with the posterior probability that the number of unemployed high-skilled workers u_h will increase being equal to .113. The overall per-period output Y will increase by 10% on average. High-skilled workers lose from the policy as their discounted present streams of income while unemployed as well as while employed all decrease. However, the policy increases the welfare of low-skilled unemployed and employed workers so that the total welfare increases with probability .67.

Figure 4.6 present some of the effects of the policy on selected labor market outcomes of workers with 12 years of education and of workers with 16 or more years of education. The figure suggests that the policy decreases the mean duration of unemployment of both educational groups, and that the level effect of the policy is more uncertain for workers with 12 years of education than for workers with 16 or more years of education. The policy also increases wages of workers with 12 years of eduction and decreases wages of workers with 16 or more years of education. The level effect on wages is more uncertain for workers with 16 or more years of education that for workers with 12 years of education.

4.7 Increase in the Proportion of High-skilled Workers

The effect of the decrease in μ by .10 is presented in Table 4.8. The probability that the cross-skill matching equilibrium will exist after this policy change, given the original prior on parameters as defined in (3.20), is 1.

Figure 4.6: Before- and After-policy Unemployment Durations and Wages, Subsidy for Employing Low-skilled Workers Financed by a Lump-sum Tax on High-skilled Workers



The left-ward shift of .10 in μ increases labor market tightness θ, which in turn increases the rate at which high-skilled workers exit unemployment $\theta q(\theta)$. This change decreases mean unemployment duration of high-skilled workers.

The increase in the proportion of skilled labor increases the probability that a complex vacancy will match with a worker, which stimulates job creation in the complex sector and decreases the fraction of simple vacancies in the mass of vacancies η. The net effect of the increase in $\theta q(\theta)$ and the decrease in η on the rate of exit from unemployment of low-skilled workers is negative: $\theta q(\theta)\eta$ on average decreases.

The effect of the policy on the direction of change in total unemployment u is uncertain: there is a 58% probability that the total unemployment will increase. The number of low-skilled unemployed u_l decreases on average, while the unemployment rate of low-skilled workers increases. This happens because the change in the skill composition of the labor force generates firm exit from the simple sector and firm entry in the complex sector. Job creation in the complex sector absorbs most of the newly trained workers.

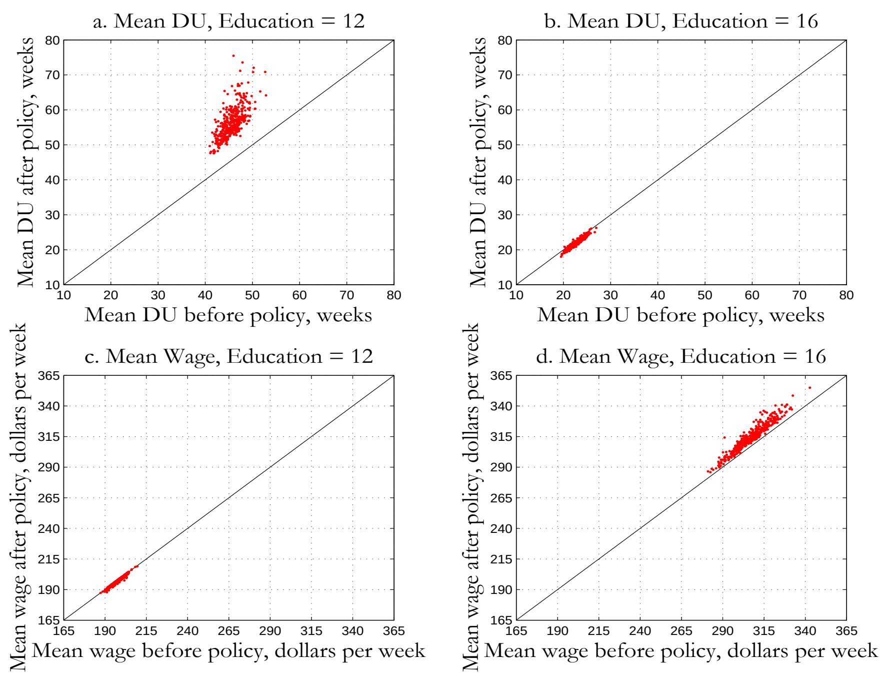
The policy increases the mean wages of high-skilled workers: $\frac{e_{s,h} \cdot w_{s,h} + e_{c,h} \cdot w_{c,h}}{e_{s,h} + e_{c,h}}$ because the composition of filled jobs changes in favor of complex jobs which pay the highest wages. The per capita weekly output of the economy Y increases, because even though the total employment does not change substantially, the share of more productive complex jobs in total employment increases. The policy is beneficial for workers who were high-skilled before it was put in place, and even more so for workers whose skill level is increased by the policy, as their expected discounted streams on income while employed and while unemployed both increase. Workers who remain low-skilled lose from the policy, as their expected income stream from unemployment and employment U_l and $W_{s,l}$ both decrease due to the decrease in wages and the exit rate from unemployment. However, the total welfare increases as a result of the policy as the gains of the part of the labor force who benefit from the policy outweigh the losses of the part of the labor force who lose from the policy.

Figure 4.7 presents the effects of the policy on selected labor market outcomes of workers with 12 years of education and of workers with 16 or more years of education. The graphs suggest that there is more uncertainty about the policy effect on the mean unemployment duration and unemployment rate of workers with 12 years of education than of those with 16 years of education, and that the uncertainty about the level effects of the policy on wages is low compared to the uncertainty about the before-policy level of wages of the workers of the two educational groups.

4.8 Increase in the Proportion of High-skilled Workers and a Subsidy for Employing Low-skilled Workers Financed by a Tax on High-skilled Workers

This section gives example of a policy that mitigates the negative effects of an increase in the proportion of high-skilled workers on labor market outcomes of low-skilled workers who remain low-skilled after the change in the skill composition of the labor force occurs, and to keep government budget balanced at the same time. As

Figure 4.7: Before- and After-policy Unemployment Durations and Wages, Increase in the Proportion of High-skilled Workers in the Labor Force



have been shown in section 4.6 it is possible to decrease the overall and the low-skilled unemployment rates by the employment subsidy for employing low-skilled workers financed by a lump-sum tax on employed high-skilled workers. This section investigates what size of a subsidy for employing a low-skilled worker and what size of a lump-sum tax on employed high-skilled workers in needed to keep the expected welfare of workers who remain low-skilled unchanged after the change in skill composition of the labor force examined in section 4.7 occurs, and to keep the expected government deficit close to zero at the same time. After experimenting with several tax-subsidy schedules I found that a subsidy of \$5 per week for employing a low-skilled worker financed by a lump-sum tax of \$5.2 per week on employed high-skilled worker is needed to keep the expected welfare of low-skilled workers approximately unchanged after the increase of proportion of high-skilled workers $1-\mu$ by .10. The probability that the cross-skill matching equilibrium will exist after this policy change, given the original prior on parameters as defined in (3.20), is 1.

Table 4.9 presents the effects of this policy mix on some of the functions of interest to a policymaker. After the policy the expected unemployment duration and rate of low-skilled workers is higher than before the policy, but this change is compensated by a higher wage as low-skilled workers appropriate a fraction of the subsidy paid to firms through the process of wage bargaining. The means of the present discounted income streams to unemployed and employed low-skilled workers do not change substantially. The expected cost of this policy is close to zero.

This policy mix increases expected output more than the policy which increases the proportion of high-skilled workers alone. This happens because the total employment in complex jobs $e_{c,h}$ after the policy mix is approximately equal to that after the change in skill composition alone, while the employment in simple jobs $e_{s,l} + e_{s,h}$ decreases less after the policy mix than after the change in the skill composition alone.

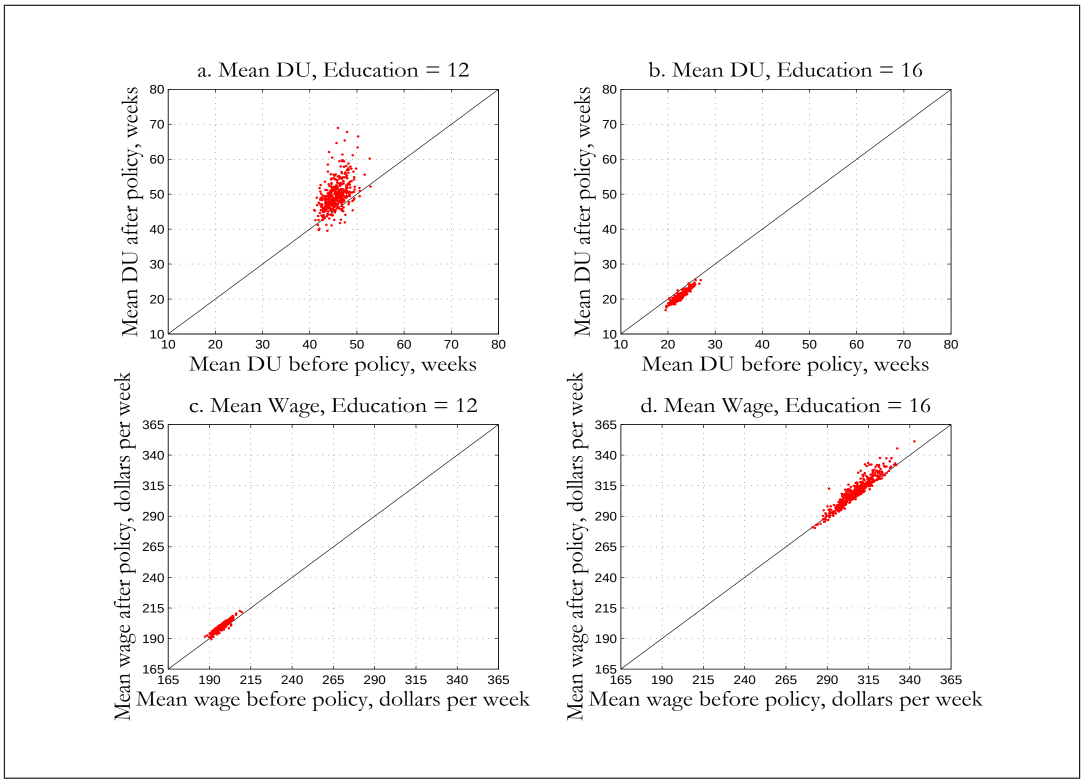
Figure 4.8 presents some of the effects of this policy mix on selected labor market outcomes of workers with 12 years of education and of workers with 16 or more years of education. The figure suggests that there is a lot of uncertainty about the effect of this policy on mean duration of unemployment of workers with 12 years of education: the predicted after-policy mean duration of unemployment of this group ranges from 40 to 70 weeks. The figure suggests that despite the lump-sum tax on high-skilled workers the mean wages of workers with 16 years of education or more will increase, as in the case of the change in skill composition alone.

4.9 Increase in Unemployment Income

The effect of the increase in unemployment income b by \$15 is shown in Table 4.10. The probability that the cross-skill matching equilibrium will exist after this policy change, given the original prior on parameters as defined in (3.20), is 1.

The increase in b increases the present discounted stream of profits to unemployed worker thus strengthening worker's position in the wage bargaining with employer. This decreases the expected stream of profits to a firm from a filled job, thus generating firm exit from the market. Labor market tightness θ and the fraction of simple jobs η both decrease. As a result, the exit rate from unemployment

Figure 4.8: Before- and After-Policy Unemployment Durations and Wages, Increase in the Proportion on High-Skilled Workers in the Labor Force and Employment Subsidy for Employing Low-skilled Workers Financed by a Lump-sum Tax on High-skilled Workers

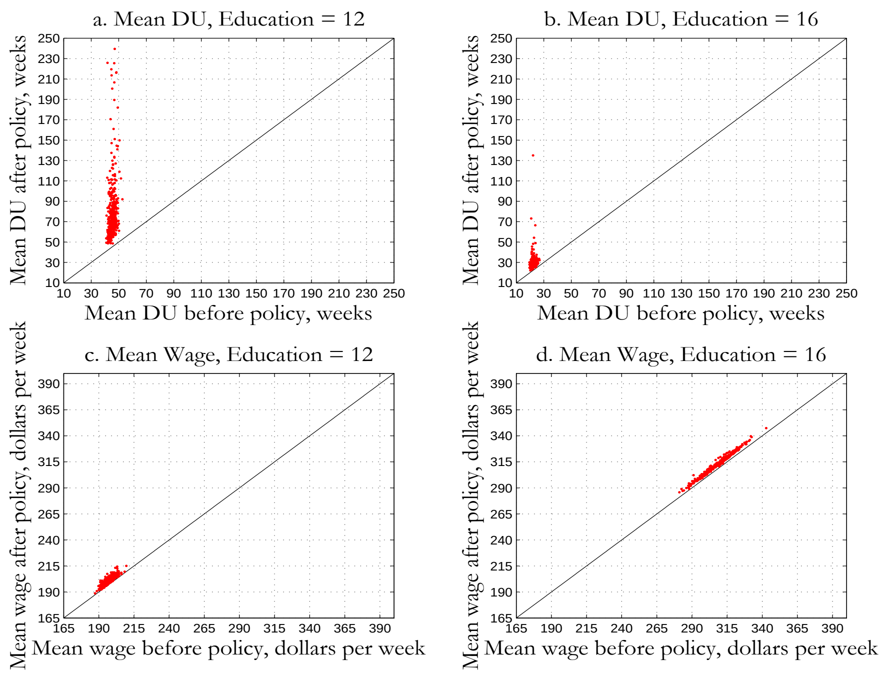


of high-skilled workers $\theta q(\theta)$ and that of low-skilled workers $\eta\theta q(\theta)$ both decrease, thus increasing mean unemployment durations of the workers of the two skill groups. The unemployment rate u increases, and the increase in unemployment is concentrated disproportionately among low-skilled workers. The increase in unemployment is caused by firm exit from the simple sector, because the number of simple jobs NF_s decreases and NF_c does not change.

Despite increased incidence of unemployment and increased unemployment duration, the expected income streams from unemployment and employment to workers of both skill types increases. Weekly per capita output Y decreases. The expected cost of the policy is about \$7.95 per worker per week, which results in the expected net loss from the policy of \$31 per worker per week.

Figure 4.9 present some of the policy effects in a way which is visually informative about the uncertainty about the equilibrium outcomes. The figure suggests that there is a huge uncertainty about the level effect of the policy on the mean unemployment durations of workers with 12 and 16 and more years of education. The predicted after-policy mean duration of unemployment ranges from 50 to 170 weeks for workers with 12 years of education while the before-policy mean duration of unemployment for this group ranges between 40 and 50 weeks. The predicted after-policy mean duration of unemployment ranges form 20 to 140 weeks for workers with 16 or more years of education while the before-policy mean duration of unemployment for this group ranges between 20 and 30 weeks. The distribution of the after-policy mean unemployment durations is more evenly spread along its range for workers with 12

Figure 4.9: Before- and After-policy Unemployment Durations and Wages, Increase in Unemployment Income



years of education than for those with 16 or more years of education. The predicted after-policy mean unemployment duration for the latter group is centered around 30 weeks with several outliers above 50 weeks. The impact of the policy on wages of workers of the two educational groups is close to zero.

Table 4.1: Functions of Interest

Function	Description
$\theta q(\theta)$	Weekly probability to meet a vacancy while unemployed,
	Weekly rate of exit from unemployment of high-skilled workers
η	Share of simple vacancies in the supply of vacancies
$\theta q(\theta)\eta$	Weekly rate of exit from unemployment of low-skilled workers
DU_l	Mean duration of unemployment of low-skilled worker, weeks
DU_h	Mean duration of unemployment of high-skilled worker, weeks
u	Unemployment rate
ϕ	Proportion of unemployed workers who are low-skilled
u_l	Proportion of low-skilled unemployed in the labor force
u_h	Proportion of high-skilled unemployed in the labor force
$\widetilde{u_l}$	Low-skilled unemployment rate:$\widetilde{u_l} = \frac{u_l}{\mu}$
$\widetilde{u_h}$	High-skilled unemployment rate: $\widetilde{u_h} = \frac{u_h}{1-\mu}$
$e_{s,l}$	Proportion of low-skilled employed workers in the labor force
$e_{s,h}$	Proportion of high-skilled mismatched workers in the labor force
$e_{c,h}$	Proportion of high-skilled correctly matched workers in the labor force
$w_{s,l}$	Wage of low-skilled workers on simple jobs, $ per week
$w_{s,h}$	Wage of high-skilled workers on simple jobs, $ per week
$w_{c,h}$	Wage of high-skilled workers on complex jobs, $ per week
U_l	Expected discounted stream of income to unemployed low-skilled worker
U_h	Expected discounted stream of income to unemployed high-skilled worker
$W_{s,l}$	Expected discounted stream of income to unemployed high-skilled worker
$W_{s,h}$	Expected discounted stream of income to mismatched high-skilled worker
$W_{c,h}$	Expected discounted stream of income to high-skilled worker on complex job
$J_{s,l}$	Expected discounted stream of profits from simple job
	filled with low-skilled worker
$J_{s,h}$	Expected discounted stream of profits from simple job
	filled with high-skilled worker
$J_{c,h}$	Expected Expected discounted stream of profits from complex job
NF_s	Amount of simple jobs in the economy: $NF_s = e_{s,l} + e_{s,h} + v_s$
NF_c	Amount of complex jobs in the economy: $NF_c = e_{c,h} + v_c$
Y	Weekly per capita output:
	$Y = y_{s,l} \cdot e_{s,l} + y_{s,h} \cdot e_{s,h} + y_{c,h} \cdot e_{c,h}$
Def	Weekly per-capita cost of a policy
$Welf$	Expected total welfare

Table 4.2: Employment Subsidy for Employing a Low-skilled Worker

F	Pre.M.	Pre.S.	Post.M.	Post.S.	Mean Δ	Std.Δ	$Mean\%\Delta$	$P_{incr.}$
$\theta q(\theta)$	0.046	0.003	0.056	0.005	0.01	0.003	21.8	1
η	0.463	0.028	0.592	0.028	0.129	0.029	28.12	1
$\theta q(\theta)\eta$	0.021	0.001	0.033	0.003	0.012	0.003	56.43	1
DU_l	47.106	2.071	30.38	2.966	-16.726	3.187	-35.45	0
DU_h	21.783	1.234	17.938	1.536	-3.845	0.706	-17.74	0
u	0.422	0.013	0.335	0.021	-0.087	0.019	-20.58	0
ϕ	0.844	0.019	0.828	0.019	-0.016	0.004	-1.91	0
u_l	0.356	0.014	0.277	0.017	-0.079	0.018	-22.08	0
u_h	0.066	0.008	0.058	0.008	-0.008	0.001	-12.4	0
$\widetilde{u_l}$	0.489	0.015	0.381	0.025	-0.108	0.023	-22.08	0
$\widetilde{u_h}$	0.242	0.018	0.212	0.02	-0.03	0.006	-12.4	0
$e_{s,l}$	0.372	0.015	0.451	0.026	0.079	0.018	21.17	1
$e_{s,h}$	0.031	0.005	0.044	0.006	0.013	0.003	42.65	1
$e_{c,h}$	0.175	0.014	0.17	0.014	-0.005	0.002	-2.88	0
$w_{s,l}$	191.31	3.14	214.57	4.17	23.25	3.19	12.16	1
$w_{s,h}$	245.22	14.64	249.78	15.22	4.55	2.12	1.85	1
$w_{c,h}$	323.86	11.9	325.06	12.05	1.2	0.81	0.37	1
U_l	293432	8911	322501	10262	29068	4046	9.91	1
U_h	456311	15296	460846	15957	4535	1650	0.99	1
$W_{s,l}$	294162	8759	323508	10121	29346	4082	9.98	1
$W_{s,h}$	457580	15297	462012	15960	4431	1657	0.97	1
$W_{c,h}$	459819	15420	464248	16040	4428	1627	0.96	1
$J_{s,l}$	699	707	926	848	227	151	40.8	1
$J_{s,h}$	1134	961	1071	950	-62	25	-8.18	0
$J_{c,h}$	3353	3357	3268	3319	-85	58	-3.22	0
NF_s	0.404	0.015	0.495	0.024	0.092	0.02	22.81	1
NF_c	0.175	0.014	0.17	0.014	-0.005	0.002	-2.88	0
Y	150.77	15.96	168.87	14.94	18.1	3.49	12.21	1
Def	0	0	12.627	0.727	12.627	0.727		1
$Welf$	339448	7306	362128	7963	22680	2854	6.68	1

Table 4.3: Hiring Subsidy for Hiring a Low-skilled Worker

F	Pre.M.	Pre.S.	Post.M.	Post.S.	Mean Δ	Std.Δ	$Mean\%\Delta$	$P_{incr.}$
$\theta q(\theta)$	0.046	0.003	0.057	0.005	0.011	0.003	22.66	1
η	0.463	0.028	0.596	0.029	0.133	0.03	29.04	1
$\theta q(\theta)\eta$	0.021	0.001	0.034	0.004	0.012	0.003	58.68	1
DU_l	47.103	2.074	29.964	3.006	-17.139	3.228	-36.33	0
DU_h	21.78	1.236	17.813	1.548	-3.966	0.726	-18.31	0
u	0.422	0.013	0.332	0.021	-0.09	0.02	-21.2	0
ϕ	0.844	0.019	0.827	0.018	-0.017	0.004	-1.97	0
u_l	0.356	0.014	0.275	0.016	-0.081	0.018	-22.74	0
u_h	0.066	0.008	0.058	0.008	-0.008	0.001	-12.81	0
$\widetilde{u_l}$	0.489	0.015	0.378	0.024	-0.111	0.024	-22.74	0
$\widetilde{u_h}$	0.242	0.018	0.211	0.02	-0.031	0.006	-12.81	0
$e_{s,l}$	0.372	0.015	0.453	0.026	0.081	0.018	21.82	1
$e_{s,h}$	0.031	0.005	0.045	0.006	0.014	0.003	44.28	1
$e_{c,h}$	0.175	0.014	0.17	0.014	-0.005	0.002	-3.01	0
$w_{s,l}$	191.30	3.14	215.66	4.33	24.36	3.45	12.74	1
$w_{s,h}$	245.26	14.66	249.98	15.28	4.72	2.22	1.92	1
$w_{c,h}$	323.84	11.90	325.08	12.07	1.24	0.83	0.38	1
U_l	293429	8910	323927	10311	30498	4312	10.4	1
U_h	456328	15301	461004	15999	4676	1712	1.02	1
$W_{s,l}$	294158	8758	324945	10166	30787	4349	10.47	1
$W_{s,h}$	457598	15302	462166	16003	4568	1719	0.99	1
$W_{c,h}$	459837	15425	464402	16081	4565	1688	0.99	1
$J_{s,l}$	697	705	-467	854	-1164	159	-579	0
$J_{s,h}$	1130	955	1065	944	-64	25	-8.47	0
$J_{c,h}$	3339	3343	3252	3304	-87	60	-3.32	0
NF_s	0.404	0.015	0.498	0.024	0.095	0.021	23.54	1
NF_c	0.175	0.014	0.17	0.014	-0.005	0.002	-3.01	0
Y	150.74	15.93	169.39	14.93	18.65	3.60	12.58	1
Def	0	0	12.903	0.847	12.903	0.847	0	1
$Welf$	339466	7319	362602	7963	23136	3033	6.82	1

Table 4.4: Employment Subsidy for a Complex Jobs

F	Pre.M.	Pre.S.	Post.M.	Post.S.	Mean Δ	Std.Δ	$Mean\%\Delta$	$P_{incr.}$
$\theta q(\theta)$	0.046	0.003	0.048	0.003	0.002	0.001	4.5	1
η	0.463	0.028	0.367	0.034	-0.096	0.02	-20.75	0
$\theta q(\theta)\eta$	0.021	0.001	0.018	0.001	-0.004	0.001	-17.21	0
DU_l	47.016	2.094	56.979	4.414	9.962	3.303	21.14	1
DU_h	21.755	1.23	20.82	1.185	-0.935	0.311	-4.29	0
u	0.421	0.013	0.453	0.017	0.031	0.009	7.43	1
ϕ	0.843	0.018	0.861	0.017	0.018	0.004	2.12	1
u_l	0.355	0.015	0.39	0.018	0.034	0.01	9.71	1
u_h	0.066	0.008	0.063	0.007	-0.003	0.001	-4.84	0
$\widetilde{u_l}$	0.488	0.015	0.536	0.021	0.047	0.013	9.71	1
$\widetilde{u_h}$	0.243	0.017	0.231	0.017	-0.012	0.003	-4.84	0
$e_{s,l}$	0.372	0.015	0.338	0.018	-0.034	0.01	-9.28	0
$e_{s,h}$	0.031	0.005	0.022	0.004	-0.009	0.002	-29.97	0
$e_{c,h}$	0.175	0.014	0.187	0.015	0.013	0.003	7.23	1
$w_{s,l}$	191.06	3.17	190.26	3.21	-0.79	0.41	-0.41	0
$w_{s,h}$	247.17	15.45	244.50	15.04	-2.67	1.29	-1.07	0
$w_{c,h}$	322.97	12.09	375.41	13.83	52.44	8.85	16.28	1
U_l	293563	8841	290712	9083	-2851	492	-0.97	0
U_h	455799	14993	522312	19128	66513	11748	14.61	1
$W_{s,l}$	294277	8689	291470	8927	-2807	493	-0.96	0
$W_{s,h}$	457091	14998	523527	19144	66436	11750	14.55	1
$W_{c,h}$	459257	15136	526645	19260	67388	11879	14.69	1
$J_{s,l}$	876	1096	914	1108	38	12	6.58	1
$J_{s,h}$	1479	1467	1390	1392	-89	79	-6	0
$J_{c,h}$	4218	4939	5095	5516	877	626	26	1
NF_s	0.404	0.014	0.36	0.019	-0.044	0.011	-10.9	0
NF_c	0.175	0.014	0.188	0.015	0.013	0.003	7.25	1
Y	154.74	23.18	147.97	23.42	-6.78	1.87	-4.46	0
Def	0	0	13.613	1.031	13.613	1.031		1
$Welf$	339688	7177	356102	7750	16414	3511	4.84	1

Table 4.5: Employment Subsidy for Employing a High-skilled Worker

F	Pre.M.	Pre.S.	Post.M.	Post.S.	Mean Δ	Std.Δ	$Mean\%\Delta$	$P_{incr.}$
$\theta q(\theta)$	0.046	0.003	0.05	0.003	0.004	0.001	9.25	1
η	0.463	0.028	0.419	0.029	-0.044	0.01	-9.53	0
$\theta q(\theta)\eta$	0.021	0.001	0.021	0.001	0	0.001	-1.16	0.373
DU_l	47.017	2.096	47.623	2.646	0.605	1.631	1.29	0.63
DU_h	21.751	1.228	19.919	1.216	-1.831	0.467	-8.42	0
u	0.421	0.013	0.419	0.015	-0.003	0.007	-0.64	0.38
ϕ	0.843	0.018	0.854	0.017	0.011	0.002	1.27	1
u_l	0.355	0.015	0.357	0.016	0.002	0.006	0.63	0.63
u_h	0.066	0.008	0.061	0.007	-0.005	0.001	-7.43	0
$\widetilde{u_l}$	0.488	0.015	0.491	0.017	0.003	0.008	0.63	0.63
$\widetilde{u_h}$	0.242	0.017	0.224	0.017	-0.018	0.004	-7.43	0
$e_{s,l}$	0.372	0.015	0.37	0.016	-0.002	0.006	-0.6	0.37
$e_{s,h}$	0.031	0.005	0.026	0.004	-0.005	0.001	-16.82	0
$e_{c,h}$	0.175	0.014	0.185	0.015	0.01	0.002	5.83	1
$w_{s,l}$	191.06	3.18	190.93	3.19	-0.13	0.19	-0.07	0.37
$w_{s,h}$	247.16	15.47	286.23	21.92	39.07	13.13	15.81	1
$w_{c,h}$	322.99	12.11	377.11	13.48	54.12	8.07	16.8	1
U_l	293578	8847	293343	8831	-235	550	-0.08	0.37
U_h	455845	14984	530017	19061	74172	12157	16.29	1
$W_{s,l}$	294291	8695	294057	8681.	-235	543	-0.08	0.37
$W_{s,h}$	457136	14990	531778	19163	74642	12309	16.35	1
$W_{c,h}$	459302	15128	534146	19157	74844	12215	16.32	1
$J_{s,l}$	873	1095	878	1101	6	9	0.16	0.63
$J_{s,h}$	1473	1464	1861	1618	387	185	37.36	1
$J_{c,h}$	4206	4939	4924	5476	718	573	19.88	1
NF_s	0.404	0.014	0.396	0.016	-0.007	0.007	-1.86	0.17
NF_c	0.175	0.014	0.185	0.015	0.01	0.002	5.85	1
Y	154.67	23.16	156.28	22.24	1.61	1.52	1.14	0.83
Def	0	0	13.597	1.03	13.597	1.03		1
$Welf$	339702	7181	360067	7611	20365	3906	6	1

Table 4.6: Hiring Subsidy for Hiring a High-Skilled Worker

F	Pre.M.	Pre.S.	Post.M.	Post.S.	Mean Δ	Std.Δ	$Mean\%\Delta$	$P_{incr.}$
$\theta q(\theta)$	0.046	0.003	0.05	0.003	0.004	0.001	9.12	1
η	0.463	0.027	0.452	0.03	-0.011	0.013	-2.43	0.202
$\theta q(\theta)\eta$	0.021	0.001	0.023	0.001	0.001	0.001	6.5	0.948
DU_l	47.06	2.045	44.266	2.612	-2.793	1.942	-5.92	0.052
DU_h	21.768	1.223	19.96	1.225	-1.808	0.434	-8.31	0
u	0.422	0.013	0.406	0.014	-0.016	0.009	-3.74	0.016
ϕ	0.843	0.018	0.848	0.018	0.005	0.002	0.6	0.997
u_l	0.355	0.014	0.344	0.015	-0.011	0.008	-3.16	0.052
u_h	0.066	0.008	0.062	0.007	-0.005	0.001	-6.82	0
$\widetilde{u_l}$	0.488	0.014	0.473	0.016	-0.015	0.011	-3.16	0.052
$\widetilde{u_h}$	0.243	0.018	0.226	0.017	-0.017	0.004	-6.82	0
$e_{s,l}$	0.372	0.015	0.384	0.017	0.011	0.008	3.03	0.948
$e_{s,h}$	0.031	0.005	0.029	0.004	-0.002	0.001	-6.63	0.044
$e_{c,h}$	0.175	0.014	0.181	0.014	0.007	0.002	3.81	1
$w_{s,l}$	191.14	3.17	191.32	3.18	0.18	0.11	0.09	0.95
$w_{s,h}$	245.79	14.71	351.75	37.27	105.96	31.06	43.1	1
$w_{c,h}$	323.46	11.98	369.42	12.26	45.96	5.62	14.24	1
U_l	293353	8821	294255	8733	902	562	0.31	0.95
U_h	455910	15250	531108	17322	75198	11656	16.53	1
$W_{s,l}$	294077	8671	294961	8585	884	549	0.3	0.95
$W_{s,h}$	457186	15259	533793	17574	76607	12021	16.79	1
$W_{c,h}$	459398	15387	534648	17257	75251	11530	16.42	1
$J_{s,l}$	809	1002	800	1005	-8	5	-2.54	0.052
$J_{s,h}$	1321	1232	-940	1764	-2261	587	-557.52	0
$J_{c,h}$	3849	4324	644	4628	-3205	322	-262.23	0
NF_s	0.404	0.014	0.413	0.016	0.009	0.009	2.28	0.812
NF_c	0.175	0.014	0.181	0.014	0.007	0.002	3.82	1
Y	153.1	20.69	157.14	19.58	4.04	1.57	2.77	1
Def	0	0	10.49	1.05	10.49	1.05		1
$Welf$	339445	7160	360019	7189	20575	3812	6.07	1

Table 4.7: Subsidy for Employing Low-Skilled Workers Financed by a Lump-sum Tax on High-skilled Workers

F	Pre.M.	Pre.S.	Post.M.	Post.S.	Mean Δ	Std.Δ	$Mean\%\Delta$	$P_{incr.}$
$\theta q(\theta)$	0.046	0.003	0.05	0.004	0.004	0.002	9.25	0.997
η	0.462	0.027	0.646	0.033	0.184	0.035	40.04	1
$\theta q(\theta)\eta$	0.021	0.001	0.033	0.003	0.011	0.003	53.23	1
DU_l	47.101	2.099	30.967	2.801	-16.134	3.021	-34.2	0
DU_h	21.759	1.25	19.963	1.646	-1.795	0.651	-8.35	0.003
u	0.422	0.013	0.345	0.02	-0.077	0.018	-18.29	0
ϕ	0.844	0.019	0.815	0.021	-0.029	0.006	-3.48	0
u_l	0.356	0.015	0.281	0.015	-0.075	0.017	-21.12	0
u_h	0.066	0.008	0.064	0.009	-0.002	0.001	-2.9	0.113
$\widetilde{u_l}$	0.489	0.015	0.386	0.023	-0.103	0.022	-21.12	0
$\widetilde{u_h}$	0.242	0.018	0.235	0.021	-0.007	0.006	-2.9	0.113
$e_{s,l}$	0.372	0.016	0.448	0.026	0.075	0.017	20.26	1
$e_{s,h}$	0.031	0.005	0.054	0.008	0.023	0.005	76.32	1
$e_{c,h}$	0.175	0.014	0.153	0.014	-0.022	0.006	-12.37	0
$w_{s,l}$	191.29	3.16	214.9	3.9	23.60	2.85	12.35	1
$w_{s,h}$	244	14.58	203.70	16.29	-40.3	11.96	-16.5	0
$w_{c,h}$	324.35	12.05	270.03	15.03	-54.32	6.22	-16.79	0
U_l	293126	8862	322153	10017	29027	3225	9.91	1
U_h	456591	15825	383503	19379	-73088	9703	-16.03	0
$W_{s,l}$	293863	8709	323185	9867	29323	3267	9.98	1
$W_{s,h}$	457846	15828	384119	19479	-73727	9869	-16.13	0
$W_{c,h}$	460127	15950	386304	19553	-73822	9733	-16.07	0
$J_{s,l}$	635	678	845	805	210	136	42.99	1
$J_{s,h}$	987	845	580	679	-407	199	-51.9	0
$J_{c,h}$	3015	3148	2440	2730	-575	444	-21.26	0
NF_s	0.40	0.02	0.50	0.02	0.1	0.02	24.54	1
NF_c	0.18	0.01	0.15	0.01	-0.02	0.01	-12.39	0
Y	149.23	15.23	163.51	14.87	14.28	3.63	9.7	1
Def	0	0	-0.44	1.51	-0.44	1.51		0.36
$Welf$	339173	7379	340444	8429	1271	2607	0.37	0.67

Table 4.8: Increase in the Proportion of High-skilled Workers in the Labor Force

F	Pre.M.	Pre.S.	Post.M.	Post.S.	Mean Δ	Std.Δ	$Mean\%\Delta$	$P_{incr.}$
$\theta q(\theta)$	0.046	0.003	0.049	0.003	0.003	0.001	6.29	1
η	0.463	0.028	0.352	0.03	-0.111	0.016	-24.04	0
$\theta q(\theta)\eta$	0.021	0.001	0.017	0.001	-0.004	0.001	-19.24	0
DU_l	47.016	2.094	58.416	4.522	11.399	3.486	24.21	1
DU_h	21.755	1.23	20.473	1.208	-1.282	0.233	-5.9	0
u	0.421	0.013	0.425	0.017	0.003	0.009	0.81	0.578
ϕ	0.843	0.018	0.8	0.021	-0.043	0.004	-5.06	0
u_l	0.355	0.015	0.34	0.018	-0.015	0.009	-4.28	0.06
u_h	0.066	0.008	0.085	0.009	0.019	0.002	28.26	1
$\widetilde{u_l}$	0.488	0.015	0.542	0.021	0.054	0.014	10.98	1
$\widetilde{u_h}$	0.243	0.017	0.227	0.017	-0.015	0.002	-6.33	0
$e_{s,l}$	0.372	0.015	0.288	0.016	-0.085	0.009	-22.8	0
$e_{s,h}$	0.031	0.005	0.028	0.005	-0.003	0.002	-10.33	0
$e_{c,h}$	0.175	0.014	0.259	0.015	0.085	0.002	48.72	1
$w_{s,l}$	191.06	3.17	189.96	3.25	-1.1	0.94	-0.57	0
$w_{s,h}$	247.17	15.45	243.82	15.6	-3.35	2.09	-1.36	0
$w_{c,h}$	322.97	12.09	327.06	13.39	4.08	3.07	1.25	1
U_l	293563	8841	290056	9655	-3508	1621	-1.2	0
U_h	455799	14993	469377	16641	13578	4579	2.97	1
$W_{s,l}$	294277	8689	290818	9486	-3460	1617	-1.18	0
$W_{s,h}$	457091	14998	470567	16624	13476	4564	2.94	1
$W_{c,h}$	459257	15136	472550	16836	13293	4591	72.89	1
$J_{s,l}$	876	1096	929	1137	52	45	6.77	1
$J_{s,h}$	1479	1467	1337	1281	-143	189	-7.95	0
$J_{c,h}$	4218	4939	3932	4736	-286	219	-8.23	0
NF_s	0.40	0.01	0.32	0.02	-0.09	0.01	-21.83	0
NF_c	0.18	0.01	0.26	0.02	0.09	0.00	48.71	1
Y	154.74	23.18	168.21	25.07	13.47	2.2	8.71	1
Def	0	0	0	0	0	0		0
$Welf$	339688	7177	359127	7673	19439	2097	5.72	1

Table 4.9: Increase in the Proportion on High-skilled Workers and a Subsidy for Employing Low-skilled Workers Financed by a Lump-sum Tax on High-skilled Workers

F	Pre.M.	Pre.S.	Post.M.	Post.S.	Mean Δ	Std.Δ	$Mean\%\Delta$	$P_{incr.}$
$\theta q(\theta)$	0.046	0.003	0.051	0.003	0.004	0.001	9.7	1
η	0.463	0.028	0.387	0.031	-0.076	0.023	-16.47	0
$\theta q(\theta)\eta$	0.021	0.001	0.02	0.002	-0.002	0.001	-8.29	0.095
DU_l	47.016	2.094	51.559	4.628	4.543	4.043	9.67	0.905
DU_h	21.755	1.23	19.847	1.302	-1.908	0.374	-8.8	0
u	0.421	0.013	0.403	0.019	-0.018	0.013	-4.26	0.083
ϕ	0.843	0.018	0.794	0.021	-0.049	0.005	-5.81	0
u_l	0.355	0.015	0.32	0.018	-0.035	0.012	-9.82	0.013
u_h	0.066	0.008	0.083	0.009	0.017	0.002	25.68	1
$\widetilde{u_l}$	0.488	0.015	0.51	0.024	0.022	0.019	4.57	0.905
$\widetilde{u_h}$	0.243	0.017	0.223	0.018	-0.02	0.003	-8.2	0
$e_{s,l}$	0.372	0.015	0.307	0.019	-0.065	0.012	-17.51	0
$e_{s,h}$	0.031	0.005	0.032	0.005	0	0.002	1.23	0.598
$e_{c,h}$	0.175	0.014	0.258	0.015	0.083	0.002	47.63	1
$w_{s,l}$	191.06	3.17	193.86	3.47	2.8	1.63	1.47	0.94
$w_{s,h}$	247.17	15.45	241.67	15.48	-5.5	0.96	-2.23	0
$w_{c,h}$	322.97	12.09	322.97	13.67	-0.01	3.81	-0.02	0.42
U_l	293563	8841	294619	9865	1055	2351	0.35	0.70
U_h	455799	14993	464386	16996	8586	5400	1.88	0.99
$W_{s,l}$	294277	8689	295436	9701	1159	2360	0.39	0.73
$W_{s,h}$	457091	14998	465519	16986	8428	5403	1.84	0.99
$W_{c,h}$	459257	15136	467482	17191	8225	5434	1.78	0.99
$J_{s,l}$	876	1096	981	1167	105	78	15.15	1
$J_{s,h}$	1479	1467	1294	1268	-186	201	-12.36	0
$J_{c,h}$	4218	4939	3854	4687	-364	272	-10.53	0
NF_s	0.40	0.01	0.34	0.02	-0.07	0.01	-16.06	0
NF_c	0.18	0.01	0.26	0.02	0.08	0.00	47.62	1
Y	154.74	23.18	172.67	24.76	17.93	2.22	11.67	1
Def	0	0	0.03	0.15	0.03	0.15		0.58
$Welf$	339688	7177	360146	7736	20458	2081	6.02	1

Table 4.10: Increase in Unemployment Income

F	Pre.M.	Pre.S.	Post.M.	Post.S.	Mean Δ	Std.Δ	$Mean\%\Delta$	$P_{incr.}$
$\theta q(\theta)$	0.046	0.003	0.037	0.003	-0.009	0.003	-18.58	0
η	0.464	0.027	0.335	0.083	-0.129	0.069	-28.24	0
$\theta q(\theta)\eta$	0.021	0.001	0.013	0.004	-0.009	0.003	-40.57	0
DU_l	47.002	2.093	104.211	189.826	57.208	189.636	120.5	1
DU_h	21.781	1.222	26.899	2.367	5.119	2.272	23.68	1
u	0.421	0.013	0.53	0.063	0.109	0.06	25.8	1
ϕ	0.843	0.018	0.855	0.02	0.012	0.006	1.45	1
u_l	0.355	0.015	0.454	0.063	0.099	0.057	27.72	1
u_h	0.066	0.007	0.076	0.008	0.01	0.004	15.14	1
$\widetilde{u_l}$	0.488	0.015	0.624	0.079	0.135	0.076	27.72	1
$\widetilde{u_h}$	0.243	0.017	0.279	0.021	0.036	0.015	15.14	1
$e_{s,l}$	0.372	0.015	0.273	0.056	-0.099	0.057	-26.54	0
$e_{s,h}$	0.032	0.005	0.022	0.007	-0.01	0.004	-32.54	0
$e_{c,h}$	0.175	0.014	0.175	0.014	0	0.001	0.05	0.393
$w_{s,l}$	191.04	3.2	194.55	4	3.51	2.19	1.83	1
$w_{s,h}$	246.76	15.08	248.85	13.81	2.09	2.62	0.89	0.80
$w_{c,h}$	323.36	11.84	324.60	12.23	1.25	1.59	0.38	0.87
U_l	293276	8685	305178	9178	11902	2403	4.06	1
U_h	455853	15045	459294	14987	3441	3653	0.76	0.87
$W_{s,l}$	293997	8539	305725	9044	11728	2437	3.99	1
$W_{s,h}$	457145	15049	460555	14982	3410	3624	0.75	0.87
$W_{c,h}$	459332	15182	462717	15186	3385	3604	0.74	0.87
$J_{s,l}$	893	1101	725	1016	-168	104	-26	0
$J_{s,h}$	1504	1471	1462	1436	-42	47	-3	0.14
$J_{c,h}$	4294	4960	4207	4854	-87	113	-1.49	0.13
NF_s	0.40	0.02	0.3	0.06	-0.11	0.06	-27.01	0
NF_c	0.18	0.01	0.18	0.01	0	0.00	0.05	0.39
Y	155.13	23.25	132	30.5	-23.12	11.51	-15.62	0
Def	0	0	7.95	0.95	0	0		0
$Welf$	339539	7140	348880	7780	9342	2446	2.75	1

CHAPTER 5

CONCLUSION

To improve labor market outcomes of less-skilled workers many countries use active labor market policies such as state-subsidized general and vocational training, hiring and employment subsidies. Because these policies may affect firms' and workers' decisions along many dimensions, a comprehensive evaluation of the potential effects of such policies is required to assess their ability to affect wages and employment of the target skill group, as well as their potential impact on labor markets outcomes of workers of other skill groups. This dissertation undertakes a quantitative study of selected labor market policies in a matching model with skill heterogeneity and on-the-job search based on the model of Dolado, Jansen, and Jimeno (2003). The main features of the model are heterogeneity of workers with respect to skill level and heterogeneity of firms with respect to skill requirement, as well as the existence of overlap between the labor markets for different skill groups in that high-skilled workers can take stepping-stone jobs in the lower-skill segment of the market. The latter feature of the model creates the possibility that labor market policies targeted at one skill group can have unintended effects on the other skill group. This set-up is motivated by studies which document the existence of spill-overs of workers into jobs with skill requirement below their skill level both in US and Europe.

The quantitative policy evaluation is based on the joint posterior distribution of structural parameters of the model using data on labor market histories of NLSY79 respondents. The information on unemployment and job durations and wages whose joint equilibrium distribution is generated by the model is utilized to obtain the joint posterior distribution of structural parameters. Simultaneously, AFQT scores of individuals and skill requirements of occupations as estimated by Ingram and Neumann (2006) are used to identify skill level of workers and skill requirement of jobs in the realized firm-worker matches in the data.

Next, the posterior distribution of the structural parameters and the model are used to evaluate the posterior distributions of policy impacts on some of the endogenous variables which might be of interest to policy-maker, such as mean duration of unemployment and unemployment rate of low- and high-skilled workers, and others. I consider the policies such as introduction of subsidies for hiring or employing low- and high-skilled workers, skill upgrading modeled as an increase in the share of high-skilled workers in the labor force, and increase in the unemployment income. I also consider combinations of these policies in policy mixes with a balanced government budget. The policy experiments amount to adding a fixed constant to an unknown structural parameter in each case. The uncertainty about the parameters translates into uncertainty about the quantitative predictions of the model with respect to impacts of the policies on the endogenous variables of interest. To take this uncertainty into account I evaluate the equilibrium effects of the policies for a range of values of structural parameters which is representative of their posterior distribution.

I find that the employment subsidy of 28 constant 1986 dollars per week for employing low-skilled workers decreases low- and high-skilled unemployment and increases wages of the two skill groups. The one-time hiring subsidy of 1400 constant 1986 dollars paid to a firm for hiring a low-skilled workers generates changes in the means of the functions of interest to a policymaker similar to those generated by the employment subsidy of 28 constant 1986 dollars per week for employing low-skilled workers. However, the variances of the predicted quantitative effects of the hiring subsidy tend to be larger than the variances of the predicted effects of the employment subsidy suggesting that a risk-averse policymaker would prefer the employment subsidy to a hiring subsidy.

The employment subsidy of 65 constant 1986 dollars per week for skilled jobs has a differential impact on low- and high-skilled unemployment: the policy increases the unemployment rates and durations of low-skilled workers and decreases those of high-skilled workers. The quantitative effects of the employment subsidy of 64.4 constant 1986 dollars for employing high-skilled workers on labor market outcomes of high-skilled workers is similar to that of the employment subsidy for complex jobs. However, the employment subsidy for employing high-skilled workers does not have the adverse affect on labor market outcomes of low-skilled workers. This suggests that when the goal of a policymaker is to increase the amount of high-tech (complex) jobs in the economy, the better strategy is to subsidize the employment of high-skilled workers than to subsidize the employment in high-tech jobs.

I also find that it is possible to decrease low-skilled and overall unemployment by introducing the subsidy for employing low-skilled workers financed by a lump-sum tax on employed high-skilled workers. With properly chosen amounts of tax and subsidy such a policy would produce zero expected deficit and would decrease the overall unemployment rate as well as the low-skilled unemployment rate.

I also find that the 10 percentage points increase in the proportion of high-skilled workers in the labor force would increase mean unemployment rate and duration of low-skilled workers whose skill level did not change after the change in the skill distribution of the labor force occurs. The employment subsidy of 5 dollars for employing low-skilled workers financed by the lump-sum tax of 5.4 dollars on employed high-skilled workers would allow to keep the welfare of low-skilled workers unchanged after the change in the skill distribution and to keep government budget balanced at the same time.

Finally, the analysis suggests that an increase in unemployment income would increase low-skilled unemployment more than high-skilled unemployment. In general, for most of the policy experiments the quantitative impact of policies on unemployment rate and duration of unemployment is more uncertain for low-skilled workers than for high-skilled workers. These counterfactual experiments illustrate that when different skill segments of the labor market overlap, the labor market policies targeted at a particular skill segment might have substantial unintended consequences for other skill segments.

APPENDIX

JOINT DISTRIBUTION TESTS

The joint distribution test for detection of errors in posterior simulators developed in Geweke (2004) is based on a formal comparison of two simulation approximations of

$$\overline{f} = E(f(\omega, \mathbf{D}) = \int_{\Omega} \int_{\mathbf{D}} f(\omega, \mathbf{D}) p(\omega, \mathbf{D}) dm(\mathbf{D}) dv(\omega)$$

for a set of test functions f which satisfy $var(f(\omega, \mathbf{D})) < \infty$, where ω is the vector of unobservables, $\mathbf{D}$ is the vector of observables and $p(\omega, \mathbf{D}) = p(\omega)p(\mathbf{D}|\omega)$ is the joint probability density of observables and unobservables.

The first simulation approximation is obtained using the marginal-conditional simulator of the joint distribution of ω and $\mathbf{D}$,

$$\begin{aligned} \omega^{(m)} &\sim p(\omega), \\ \mathbf{D}^{(m)} &\sim p(\mathbf{D}|\omega), \\ f^{(m)} &= f(\omega^{(m)}, \mathbf{D}^{(m)}). \end{aligned} \tag{A.1}$$

The sequence $\left\{\omega^{(m)}, \mathbf{D}^{(m)}\right\}$ produced by this simulator is i.i.d.

The second simulation approximation is obtained using the successive-conditional simulator of the joint distribution of ω and $\mathbf{D}$. This simulator starts with the initial draw $\widetilde{\omega}^{(0)} \sim p(\omega)$ and proceeds with the successive iterations

$$\begin{aligned} \widetilde{\mathbf{D}}^{(m)} &\sim p(y|\omega^{(m-1)}) \\ \widetilde{\omega}^{(m)} &\sim p(\omega|\widetilde{\omega}^{(m-1)}, \widetilde{\mathbf{D}}^{(m)}) \\ \widetilde{f}^{(m)} &= f(\widetilde{\omega}^{(m)}, \widetilde{\mathbf{D}}^{(m)}) \end{aligned} \tag{A.2}$$

where $p(\omega|\widetilde{\omega}_{\mathbf{D}^o}^{(m-1)}, \mathbf{D}^o)$ is the transition density of the Markov chain which produces the sequence of simulations $\left\{\widetilde{\omega}_{\mathbf{D}^o}^{(m)}\right\}$ from the posterior distribution of ω given the observed data $\mathbf{D}^o$.

If both simulators are error-free and the chain $\left\{\widetilde{\omega}^{(m)}, \widetilde{\mathbf{D}}^{(m)}\right\}$ is uniformly ergodic, then as the number of iterations in the marginal-conditional simulation $M_1 \to \infty$ and the number of iterations in the successive-conditional simulation $M_2 \to \infty$,

$$z = \left(\overline{f}^{(M_1)} - \overline{\widetilde{f}}^{(M_2)}\right) / \left(M_1^{-1}\widehat{\sigma}_f^{2(M_1)} + M_2^{-1}\widehat{\tau}_f^{2(M_1)}\right)^{1/2} \xrightarrow{d} N(0,1) \tag{A.3}$$

where $\overline{f}^{(M_1)} = M_1^{-1}\sum_{m=1}^{M_1} f^{(m)}$, $\overline{\widetilde{f}}^{(M_2)} = M_2^{-1}\sum_{m=1}^{M_2} \widetilde{f}^{(m)}$, $M_1^{-1}\widehat{\sigma}_f^{2(M_1)} = \sum_{m=1}^{M_1}\left(f^{(m)}\right)^2 - \left(\overline{f}^{(M_1)}\right)^2$ and $M_2^{-1}\widehat{\tau}_f^{2(M_1)}$ is the square of the numerical standard error of $\overline{\widetilde{f}}^{(M_2)}$ proposed by Geweke (1992).

The joint distribution test of the MCMC algorithms developed in chapter 3 of this thesis proceeds as follows. The vector of parameters ω is defined in chapter 3:

$$\omega = [\theta q(\theta), \eta, \delta_s, \delta_c, \boldsymbol{\gamma}', \mathbf{h}', b, y_{s,l}, y_{s,h}, y_{c,h}, \kappa, \beta, \boldsymbol{\pi}_l', \boldsymbol{\pi}_h', q]'.$$

As discussed in section 3.3.1, it is not necessary to develop the posterior inference for the probability q of missing duration of unemployment DU_i because the observed collection of data $\{DU_i^o\}_{i=1}^{N^o}$, $\{DJ_i\}_{i=1}^{N}$, $\mathbf{e}$, $\mathbf{EDU}$ is an ancillary statistic with respect to q, and the counterfactual labor market outcomes which constitute the vector of interest of the analysis in this thesis do not depend on q. However, a value of q is required to generate observations from (A.1) and (A.2). I set $q = .16$ where .16 is a number close to the sample proportion of observations with missing unemployment durations.

The marginal-conditional simulator draws the vector of the remaining parameters ω_{-q} from the prior defined in (3.20)-(3.30). The successive-conditional simulator alternates between the simulation of $[DU_i^o, DJ_i, lnw_i, afqt_i, f1_i, I_i]$ conditional on the unobservables ω and the latent state assignment k_i, and an iteration of the MCMC algorithm described in section 3.3.2. Test functions involve only parameters, therefore it is not necessary to generate $\mathbf{D}^{(m)}$ in the marginal-conditional simulation. There are 740 test functions: all 37 elements of the vector $\mathbf{f} = [\omega'_{-q}, \phi, u, e_{s,h}, \psi]'$, where ϕ, u, $e_{s,h}$ and ψ are computed conditional on ω_{-q} from the steady-state conditions (2.10)-(2.12), and all unique elements of the array $\mathbf{f} \cdot \mathbf{f}'$. The marginal-conditional simulation employed $M_1 = 10^4$ replications. The successive-conditional simulator employed $N = 4$ observations and 5×10^6 iterations of which every 1000'th iteration was recorded to remove serial correlation. Tables A.1-A.3 present the absolute values of the test statistics z defined in (A.3) computed for all unique elements of $\mathbf{f}$ and $\mathbf{f} \cdot \mathbf{f}'$. The elements of $\mathbf{f}$ are indicated in the first rows and columns of Tables A.1-A.3. The test statistics in the second column of Table A.1 correspond to the elements of $\mathbf{f}$ and involve no interactions between the elements of $\mathbf{f}$. The remaining statistics in Tables

A.1-A.3 correspond to the elements of $\mathbf{f} \cdot \mathbf{f}'$ indicated by the first rows and columns. The entries exceeding 2.5758 are underlined, there are 19 such entries in the three tables. A Bonferroni test of the null hypothesis that the two simulators are the same for all 740 test functions rejects the null at 5% significance level if any test statistic in Tables A.1-A.3 is greater than $\Phi^{-1}(.05/(2 \cdot 740)) = 3.9847$. None of the statistics in Tables A.1-A.3 exceeds 3.9847, so the null hypothesis of the Bonferroni test that the two simulators are the same cannot be rejected at 5% significance level.

Table A.1: Results of the Joint Distribution Test, Part 1

f	1	b	$y_{s,l}$	$y_{s,h}$	$y_{c,h}$	κ	ϕ	u	$e_{s,h}$	ψ	δ_s	δ_c	β	η
b	1.5													
$y_{s,l}$	1.6	1.3	1											
$y_{s,h}$	0	0.5	1.1	0.6										
$y_{c,h}$	0.5	0.8	1	0.5	0.9									
κ	0.9	0.4	1	0.6	1	1								
ϕ	0.5	1.4	1.9	0.1	1	0.7	0.7							
u	1.6	2.5	1.2	1.2	0.7	0.9	1.9	1.1						
$e_{s,h}$	0.9	0	0.4	0.7	0.7	0.9	1.9	0.6	0.8					
ψ	2.2	1.4	1.5	0.1	0.6	0.9	1	1.6	1.2	1.8				
δ_s	0.6	$\underline{2.8}$	2.4	0.7	0.8	1.2	0.4	0.5	2.3	0.5	0.1			
δ_c	0.8	1.5	1	1.2	0.6	1.3	0.7	0.4	0.2	0.6	0.8	0.4		
β	1.2	0.2	1	1.7	$\underline{3.7}$	0	1.7	0.9	1.1	1.7	0.1	1	1.1	
η	1.3	2.1	2.3	0.7	0.3	0.9	0.8	2.2	0.8	0.9	1	1.2	0.1	1.5
μ	0.9	2.1	1.9	0.3	0.5	0.7	0.4	2	1.6	0.4	0.8	0.6	0.3	1.7
$\theta q(\theta)$	1.3	0.1	1	0.2	1.2	1	1.2	0.1	$\underline{2.7}$	1.3	0.1	0.1	1.4	0.4
$w_{s,l}$	2.2	0.3	1.4	0.9	0.6	0.9	2.1	2	0.4	2	$\underline{3.1}$	1.4	0.8	$\underline{2.7}$
$w_{s,h}$	0.8	0.2	1	0.5	1.6	0.3	1	1.7	0.6	1	1	1.5	1.8	0
$w_{c,h}$	$\underline{2.6}$	1.8	0.9	0.8	1.8	0.7	$\underline{2.7}$	0.2	0.3	$\underline{2.7}$	0.8	0.4	$\underline{3.9}$	1.3
x_l	0.3	1.1	1.3	0.3	1.4	0.3	0.5	1.1	1.3	0.4	0	1.1	0.8	0.1
x_h	1.3	0.3	1	1	1	0.9	1.2	0.2	0.3	1.5	0.9	0.4	1.1	0.5
y_s	0.7	1.8	1.3	0.8	1.5	0.6	0.7	1	0.6	0.8	0.4	0.3	1.1	0.1
y_c	0	0.2	1.5	0.4	0.8	0.8	0	1.4	0.1	0.1	0.1	0.8	0.8	0.7
$h_{w,1}$	1.9	0.4	0.2	1.4	$\underline{3.2}$	1.3	2.1	0.3	0.7	2.1	1	0.3	1.6	2
$h_{w,2}$	0.9	0.8	0.9	0.3	2	0.5	0.8	0.9	0.3	0.9	0	1	1.3	0.1
$h_{w,3}$	1.3	0.3	1.3	2	1.3	0.8	1.6	0.5	0.8	1.5	0.8	0.4	1.4	0.4
$h_{afqt,l}$	1	0.4	0.1	1.5	$\underline{2.8}$	0.7	1.2	0.2	0.2	1.1	0.7	1	0.8	1.1
$h_{afqt,h}$	0.1	0.9	1.7	0.3	0.2	0.6	0.1	1.6	0.1	0	0.3	0.7	0.3	0.5
$h_{f1,s}$	0.7	0.4	1.2	0.8	0	0.8	0.5	0.3	0	0.7	0.1	0.1	0.9	0.1
$h_{f1,c}$	0.8	0.4	1.3	0.8	0.1	1.2	0.4	0.4	0.2	0.9	0.2	0.4	1.8	0.1
π_{l1}	0.7	1.6	1.6	0.4	0.3	1.1	0.5	1.9	1	0.4	1	1.1	0.2	1.9
π_{l2}	1.2	2.3	1.7	0.4	0.3	0.9	0.5	1.6	1.3	0.9	0.4	0.7	0.2	1.4
π_{l3}	0.5	1.2	1.4	0	1.4	0.6	0.7	0.8	0.5	0.6	0.1	0.2	0.8	0.1
π_{l4}	1.5	0.8	1.1	0.5	0.8	0.7	1.1	0.7	0.2	1.7	0.6	0.4	1.4	0.1
π_{h1}	1.4	0.3	1.1	0.2	0.2	0.9	1.4	0.7	0.1	1.6	0.7	0.4	1.5	0
π_{h2}	0.5	0.8	1.7	0.2	0.4	0.8	0.3	1.7	1.1	0.3	1.1	0.9	0.1	1.1
π_{h3}	0.2	2	2	0	1	1	0.3	0.9	1.3	0.1	0	0.9	0.4	0.3
π_{h4}	0.6	1.5	2.1	0.6	0.4	0.6	0.6	1.5	0.6	0.5	0.2	0.9	0.4	1.6

Table A.2: Results of the Joint Distribution Test, Part 2

f	μ	$\theta q(\theta)$	$w_{s,l}$	$w_{s,h}$	$w_{c,h}$	x_l	x_h	y_s	y_c	$h_{w,1}$	$h_{w,2}$	$h_{w,3}$	$h_{afqt,l}$
μ	1.1												
$\theta q(\theta)$	0.9	1.2											
$w_{s,l}$	2.5	0.6	0.7										
$w_{s,h}$	0	0.9	0.1	1.2									
$w_{c,h}$	2.5	1.8	1.1	$\underline{2.6}$	2.2								
x_l	0.3	0.4	0.7	0.1	2.3	0.4							
x_h	0.4	1.2	0.5	1	2.5	0.7	1.1						
y_s	0.2	2.5	1	0.3	1.9	0.5	0.9	1.2					
y_c	1	0.8	0.7	0.6	1.6	0.5	1.2	0.6	0.2				
$h_{w,1}$	1.5	1.9	0.1	1.8	$\underline{3.4}$	0.7	2.4	0.9	0.8	0.6			
$h_{w,2}$	0.1	1.6	0.5	0.7	$\underline{2.8}$	0.5	1.3	0.2	0.4	0.7	0.5		
$h_{w,3}$	1	1.6	1.1	2.2	2.3	0.9	0.9	0.9	0.2	2.1	0.9	0.6	
$h_{afqt,l}$	1.3	1.6	0	1.4	$\underline{3}$	0.5	1.8	1.5	2	1.1	0.8	1.1	0.3
$h_{afqt,h}$	0.8	0.6	1.2	0.5	1.2	0.8	0.6	1.1	0.5	1.1	1.6	0.9	0.6
$h_{f1,s}$	0.4	1.9	0.4	1.2	1.5	0.9	0.8	0	0.6	0.8	1.2	0.9	0.3
$h_{f1,c}$	0.2	1.1	0.3	0.4	1.2	0	1.4	1.4	0.3	0.6	0.9	1.4	0.9
π_{l1}	1.1	0.1	2.4	0.2	1.8	0.1	0.8	1	0.5	1.8	0.6	0	0.4
π_{l2}	1.1	1.1	$\underline{2.7}$	0.3	1.6	0.5	0.5	0	0.1	0.4	0	0.1	0.3
π_{l3}	0.2	1.1	1.5	0.6	1.6	0.4	0.8	0.3	0.1	1.7	0.7	2.3	1.2
π_{l4}	0.3	1.4	0.4	2.1	$\underline{3}$	1.4	1.6	0.9	0.5	2.1	1.6	1.9	1.3
π_{h1}	0.5	1.4	0.7	1.3	$\underline{2.9}$	0.6	1.8	1.4	0.9	2.3	1.1	1.3	1.9
π_{h2}	0.8	1.3	1.7	0.9	1.5	0.6	0.3	0.4	0.2	0.5	0.2	1.3	0.4
π_{h3}	0.2	0.4	2.4	0.1	1.8	0.6	1	0.2	0	$\underline{2.6}$	0.4	0.6	0.7
π_{h4}	1.1	0.7	1.4	0.1	1.7	0.5	0.6	0.2	0.6	0.4	1.1	0.6	0.3

Table A.3: Results of the Joint Distribution Test, Part 3

f	$h_{afqt,h}$	$h_{f1,s}$	$h_{f1,c}$	π_{l1}	π_{l2}	π_{l3}	π_{l4}	π_{h1}	π_{h2}	π_{h3}	π_{h4}
$h_{afqt,h}$	1										
$h_{f1,s}$	0	0.4									
$h_{f1,c}$	0.9	1	1.5								
π_{l1}	0	0.2	0.3	0.4							
π_{l2}	0.5	0.2	0.6	1.5	1.6						
π_{l3}	0.3	1.2	1.4	0.3	0.2	0.8					
π_{l4}	0.1	0.9	1.3	0.1	1	0.5	1.7				
π_{h1}	0.5	1.1	1.5	0.1	0.9	0.7	1.8	1.4			
π_{h2}	0.1	0.2	0.2	0.8	1.1	0.2	0.9	0.3	0.3		
π_{h3}	0.3	0.7	0.2	0.1	1.4	0.4	0.7	0.3	0.1	0.5	
π_{h4}	0.6	0.1	1	1	1.3	0.3	0.4	0.9	1.5	0	0.7

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