

ESSAYS ON ESTIMATED LABOR SEARCH MODELS

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By

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## ESSAYS ON ESTIMATED LABOR SEARCH MODELS

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### ABSTRACT

Search theory has proven to be a very useful tool to analyze and understand the impact of labor market policies and institutional arrangements on labor market outcomes. Structural econometrics, on the other hand, seeks to recover the primitives of economic theory and to estimate decision rules. These essays use the conjunction of both to analyze various labor market issues. The first chapter estimates a search and matching model to analyze the relationship between duality in the labor market and labor market protection in Chile. Results indicate that both types of contracts, permanent and temporary, survive in equilibrium and that there is a strong substitution effect between contracts. Also, stringent labor protection generates important trade offs between flexibility and productivity. The second chapter provides lifetime measures of inequality for Chile and analyzes its main sources. Results indicate that inequality is not only high in a cross-section perspective, but also in a lifetime perspective and that low mobility is the main source of lifetime inequality. Finally, the third chapter uses a descriptive approach and a structural estimation of a search model to identify the sources of gender differentials in the United States. Results show that prejudice may still have a role in explaining the evidence on gender differentials and it is responsible for the reversal of the returns to schooling ranking in recent years.

INDEX WORDS: Labor Markets, Search Models, Structural Estimation.

## DEDICATION

This dissertation is dedicated to my family. To my beloved wife, Haydée, whose unconditional love, friendship and support are an essential pillar of my life. To my son, Cristian, who has shown me that love can go beyond the imaginable. To my mother, Teresa, who taught me the basic values of perseverance and hard work. Many thanks.

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## CHAPTER 1

### INTRODUCTION

Search theory has proven to be a very useful tool to analyze and understand the impact of labor market policies and institutional arrangements on labor market outcomes. Structural econometrics, on the other hand, explicitly combines economic theories with statistical models to recover the primitives of economic theory and to estimate decision rules derived from the models. The conjunction of both search theory and structural econometrics is almost natural and has proven to be a very powerful tool. The strengths of this combined approach are twofold: first, the assessment of policies is less vulnerable to the Lucas critique and second, it allows for the construction of counterfactual scenarios. These essays structurally estimate search models to analyze various labor market issues in developing countries and in the United States.

The first chapter estimates a search and matching model to analyze the relationship between duality in the labor market (permanent vs. temporary contracts) and labor market protection in an emerging economy (Chile). This problem has been analyzed extensively for European countries and the duality in general has been treated as exogenously determined. In the last twenty years, however, temporary arrangements have proliferated in developing nations and this phenomena seems to be an equilibrium response to reintroduce flexibility in the presence of protection of permanent jobs. Results indicate that both types of contracts survive in equilibrium and that there is a strong substitution effect between contracts. Also, stringent labor protection generates important trade offs between flexibility and productivity.

The second chapter provides lifetime measures of inequality for an emerging economy (Chile) and analyzes its main sources. In particular, a model with off and on the job search is structurally estimated with Chilean data and career simulations are used to construct lifetime measures of inequality. The lifetime inequality perspective is relevant because it reflects the long run resources available to individuals. Results indicate that inequality is not only high in a cross-section perspective, but also in a lifetime perspective. Low mobility is the main source of lifetime inequality in the Chilean labor market being the older workers who experience the lowest degree of mobility. Finally, regulation of the labor market is important because it affects the degree of mobility in the labor market.

Finally, the third chapter uses a descriptive approach and a structural estimation of a search model of the labor market to identify and quantify the impact of employers' prejudice on gender differentials (pre and in the labor market) in the United States. It also connects the findings to recent policy interventions in the US labor market presenting results of policy experiments. Results show that prejudice may still have a role in explaining the evidence on gender differentials and that there is at least one scenario where the possibility of the presence of prejudiced employers in the labor market has substantial effects. In particular, it is responsible for the reversal of the returns to schooling ranking in recent years and it may explain up to 44% of the gender wage gap of the top education group.

## CHAPTER 2

### DUAL LABOR MARKETS AND LABOR PROTECTION IN AN ESTIMATED SEARCH AND MATCHING MODEL

#### 2.1 INTRODUCTION

Temporary contracts are widely used in European countries, and in the last twenty years, have proliferated in developing nations, particularly in Latin American countries [Harrison and Leamer, 1997, Heckman and Pages, 2000]. They have been used to introduce flexibility in the labor market in order to reduce unemployment. However, the literature has found an ambiguous effect of temporary contracts on unemployment because these contracts not only affect the flows out of unemployment but also the flows out of employment for newly hired workers [see for example, Bentolila and Dolado, 1994, Blanchard and Landier, 2002, Güell, 2003, Aguirregabiria and Alonso-Borrego, 2009, among others]. At the same time, labor protection, in the form of firing costs, has also been extensively used to reduce unemployment with the difference that this policy leads to fewer job destructions. The literature has also found that labor protection affects the job creation rate generating an ambiguous effect on unemployment [see for example, Mortensen and Pissarides, 1994, 1999b, among others]<sup>1</sup>.

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<sup>1</sup>There is an exception that occurs in the absence of perfect insurance markets where employment protection (chosen optimally) plays a role of insurance and the job creation rate is not affected [Pissarides, 2001].

A large part of the literature that analyzes both temporary contracts and labor protection policies has treated the use of temporary contracts as exogenous. Little attention has been given to the endogenous relation between the two policies. In this line of the literature, the closest paper to this research is Cahuc and Postel-Vinay [2002]. However, data for some OECD and Latin American countries suggest that temporary contracts are actually used to reintroduce some flexibility when firing costs are high. In a way, this implies that employers try to avoid firing restrictions by replacing permanent with temporary workers [Harrison and Leamer, 1997]. This idea is captured in Figure 2.1 where there is a positive relation between the degree of protection of permanent jobs and the share of temporary contracts<sup>2</sup>. Hence, the following question arises: Once the government authorizes the use of temporary contracts, are these contracts an equilibrium response of firms to introduce flexibility when firing costs are high? An interest in this endogenous relation has emerged only recently, and the related literature is still scarce [see Cao et al., 2011, Alvarez and Veracierto, 2012, Macho-Stadler et al., 2011, Paolini and de Tena, 2012].

In addition to the policy implications of temporary contracts, there are concerns regarding the use of these contracts in Latin American countries since they represent a phenomenon of job insecurity (like informality) and can potentially have important effects on productivity and growth. In particular, they are associated with lower investment in human capital and productivity losses because the lack of attachment to the firm reduces the incentive of firms to invest in workers [Heckman and Pages, 2000]. Empirically, Carpio et al. [2011], in their analysis of the Chilean labor market, find that having a temporary contract reduces the probability of receiving employer-paid training. Dolado and Stucchi [2008] also find, for the case of Spain, evidence of an

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<sup>2</sup>The degree of protection is captured by the index constructed by Pierre and Scarpetta [2004].

impact of temporary jobs on total productivity; however, their mechanism is different. In their case, temporary contracts reduce the effort of workers if the probability of becoming a permanent worker is low. Therefore, following this line of the literature, temporary contracts generate a trade off between flexibility and productivity gains.

This chapter tries to answer the following questions: Can temporary contracts emerge in equilibrium when firing costs exist in a model with search frictions? Given the trade off between flexibility and productivity, do firms find it more attractive to hire on a contingent basis? In dual labor markets (that is, with permanent and temporary contracts), are agents better off and labor market outcomes less unequal? In an effort to answer these questions, this chapter extends the work presented in Mortensen and Pissarides [1994], and proposes a search and matching model with dual labor markets, in which the use of both temporary and permanent contracts is endogenously determined as part of the equilibrium.<sup>3</sup> Furthermore, the proposed model includes firing costs in the form of severance taxes to analyze the effect of labor protection policy on the equilibrium share of both types of contracts. Finally, to capture the trade off between flexibility and productivity, the model includes, in a very simple way, a mechanism of productivity gains only for permanent jobs. The model is then structurally estimated using likelihood methods with supply side data on the Chilean labor market. To quantitatively evaluate the role of labor protection legislation and the use of temporary contracts in unemployment, welfare and inequality, the chapter presents counterfactual exercises.

There are at least four reasons for working with Chilean data. First, Chile is one of the developing countries in which there was an important proliferation of contingent

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<sup>3</sup>In the model, the distinction between the two types of contracts is related to the degree of flexibility and not to the degree of formality (or informality) of the labor market. In this chapter, both types of contracts are related to formal jobs.

work arrangements in the 1990s<sup>4</sup>, and that period also coincides with an increase in firing costs. Second, aside from Brazil, Chile is one of the countries with the highest and more persistent levels of income inequality, not only at the regional level but also worldwide. Third, the level of informality in the Chilean labor market is one of the lowest for Latin American standards - less than 20% of employment is in the informal sector [Puentes and Contreras, 2009]. Finally, for estimation purposes it is necessary to have information on labor market transitions, and the Chilean Social Protection Survey used in this chapter is the only known longitudinal data for a Latin American country.

The model departs from the existing literature in two main aspects. First, this chapter does not apply the commonly used definition of temporary contracts in the literature, which links this type of contract with fixed-term contracts. Instead, the analysis uses a more broad definition of temporary contracts. In particular, these contracts have a predefined duration (possibly more than 12 months), are not subject to firing costs, and are not necessarily converted to a permanent one at the end of the contract. This distinction is relevant for Latin American countries where a large proportion of the labor force is involved in agriculture and other primary activities making fixed-term contracts less relevant than per-service or seasonal jobs<sup>5</sup>. Second, it is assumed that there are two types of jobs in the market, permanent and temporary.

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<sup>4</sup>Tables 2.1 to 2.5 show descriptive evidence on the importance of these types of contracts in the Chilean labor market using a cross-section household survey, which is representative at the national level, called the Socio-Economic Characterization Survey (CASEN). The main facts that arise from this data are: (1) temporary contracts are important even for skilled workers (they represent 35% of all jobs), (2) temporary contracts are important regardless of worker age, (3) temporary contracts last on average less than permanent contracts but more than 12 months, (4) workers with permanent contracts earn more on average, but there are also workers with temporary contracts earning high wages, (5) temporary contracts have higher prevalence in some sectors, particularly among the unskilled workers.

<sup>5</sup>For example, in the case of the Chilean labor market, fixed-term contracts represent only 13% of temporary contracts, and in the case of the Mexican labor market, the proportion of fixed-term contracts is even lower, 9.3%.



Therefore, a productivity (and wage) distribution is associated with each type of job. This implies that some jobs are done by workers hired under a permanent contract and others are done by workers hired on a temporary basis. This assumption allows for the fitting of overlapped wage distributions, similar to the ones found in the Chilean labor market<sup>6</sup>. Indeed, as Kalleberg [2000] suggests, temporary workers earn, on average, lower wages, but because there is considerable heterogeneity in the wages for temporary workers, it is possible to find jobs in which temporary worker earnings are higher than those of regular employees.

Finally, in the estimation process there are observed heterogeneity controls because there is evidence that the wage gap between temporary and permanent jobs depend on education and gender [Felgueroso and De la Rica Goiricelaya, 1999]. In particular, the sample used in this chapter is comprised of males who are unskilled (without a college degree), since the higher wage gaps are usually found in the bottom of the distribution [Bosio, 2009].

The results obtained show that given the estimated parameters, both temporary and permanent contracts survive in equilibrium and that temporary contracts are used by firms to reintroduce flexibility when there is an increase in firing costs. There is a strong substitution effect between contracts. However, temporary contracts negatively affect the frequency with which regular jobs arrive, offsetting any positive effect of firing costs on unemployment, and generating persistent inequality. Finally, temporary contracts increase flexibility but do not make workers and firms better off (there are

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<sup>6</sup>However, if it is assumed that there is one productivity distribution and the firm chooses the type of contract after observing the productivity, as in Cao et al. [2011], permanent workers will always have higher productivities (and wages) than temporary workers. As a result, it is not possible to have overlapping wages (that is, workers earning more in temporary jobs than in permanent ones).

important productivity gains in regular jobs). Welfare gains from temporary contracts are observed only if labor protection is stringent.

## 2.2 THE MODEL

This section describes the model setup and the determination of the steady state equilibrium. The model used in this chapter is an extension of Mortensen and Pissarides [1994], which considers both temporary and permanent contracts that are endogenously determined as part of the equilibrium<sup>7</sup>. This model assumes that time is continuous and that the economy is populated by infinitely lived workers, who are risk neutral and ex-ante homogenous. There is also a continuum of firms that produce their output with a fixed-coefficient technology using only labor as input. In addition, it is assumed that the labor market environment is stationary and that the search process is random. Search frictions are characterized by a matching function, which depends on the overall market tightness and the proportion of available vacancies in each type of contract. The model further assumes that there are two invariant worker-firm productivity distributions: one for each type of contract<sup>8</sup>. Once a firm meets a worker, a match-specific productivity, conditional on the type of contract, is drawn from the relevant productivity distribution, previously mentioned, and wages are determined by Nash bargaining. Only unemployed workers search for jobs, that is, there is no on-the-job search in the model.

The main differences between permanent and temporary contracts are due to employment protection legislation and productivity gains. Permanent contracts are

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<sup>7</sup>The model in Mortensen and Pissarides [1994], aside from being the standard tool in the literature for labor market policy analysis [Albrecht et al., 2009], studies the interaction between labor market protection and endogenous job destruction, which is particularly relevant for the analysis in this chapter.

<sup>8</sup>This assumption allows for the fitting of cases in which productivities overlap across contracts.

related to regular jobs, for which there is no specified term in the contract and there is job protection in the form of firing costs. Additionally, workers with permanent contracts are subject to idiosyncratic productivity shocks, which can be positive or negative. Positive shocks are interpreted as productivity gains<sup>9</sup>, while negative shocks can lead to a destruction of the worker-firm match, implying that permanent contracts are subject to endogenous job destruction.

On the other hand, this chapter departs from the widely used definition of temporary contracts in the literature, in which these contracts are considered to have a fixed-term characteristic [see for example, Cahuc and Postel-Vinay, 2002, Cao et al., 2011]<sup>10</sup>. Instead, this chapter (following the discussion from the previous section) follows Wasmer [1999], which presents a more general definition of temporary contracts. More specifically, these contracts are defined-duration contracts with contract-specific durations. This implies that these contracts can last a finite number of periods (possibly more than one) and two contracts can differ in their durations. Temporary contracts can be terminated, at no cost, either because the maximum duration expires or by a destruction shock; both cases are treated as an exogenous termination. Finally, it is assumed that firms do not transform this type of contract into a permanent contract.

The introduction of firing costs, in the form of severance tax payments, has important implications on wage determination, since firing costs change the threat point in the Nash bargaining game. In particular, if a firm with a permanent contract meets a worker, then they bilaterally bargain the wage; and if the job is not created (due to

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<sup>9</sup>In particular, these productivity gains can be interpreted as human capital investments, which exist in this type of contract given the incentives provided by a permanent contractual relation [Heckman and Pages, 2000].

<sup>10</sup>In a fixed-term contract, as defined in the literature, the job lasts for one period and can be converted to a permanent contract upon its expiration date, at no cost.

a bad productivity draw) then both the worker and the firm continue the searching process without any severance tax payment. On the other hand, if a worker is currently employed with a permanent contract and he receives a productivity shock, then the worker and the firm engage in a wage renegotiation process. However, in this case the firm has to pay the severance tax if the job is destroyed; therefore, the bargaining position of the worker is better (the outside option of the firm is different in both cases). Following the same terminology as in Pissarides [2000], a newly hired worker is called an outsider worker, while a continuing employee is called an insider worker. Additionally, payroll taxes exist on both sides of the market. As in Albrecht et al. [2009], and to simplify the analysis, it is assumed that the collected taxes, both payroll and severance, are not redistributed among workers and are just *thrown into the ocean*.

It is important to mention that the distinction between the two types of contracts is related to the degree of flexibility and not to the degree of formality (or informality) of the labor market. Both types of contracts are related to formal jobs.

### 2.2.1 WORKERS'S VALUE FUNCTIONS

At any point in time, workers can be in any one of the following four states: unemployed, employed as a new hire with a permanent contract (indexed by  $OP$ , outsider permanent), a continuing employee with a permanent contract (indexed by  $IP$ , insider permanent), and employed as a new hire with a temporary contract (indexed by  $T$ ). Let  $u$  be the rate of unemployment, and  $v_P$  and  $v_T$  be the job vacancy rates with permanent and temporary contracts, respectively. Therefore, the total vacancy rate is  $v = v_P + v_T$ . If the population is normalized to 1, then the rates at which workers and firms potentially match are  $m(u, v_P)$  and  $m(u, v_T)$ , respectively;  $m(\cdot)$  is the matching function, which is increasing in both arguments, concave and homogeneous of degree

one. Defining the overall labor market tightness as  $q = \frac{v_P+v_T}{u}$  and the proportion of permanent contract vacancies with respect to the total number of vacancies as  $\eta = \frac{v_P}{v_P+v_T}$ , and using the homogeneity property of the matching function, it is possible to write the rates at which unemployed workers meet job vacancies with permanent and temporary contracts as  $\alpha_w^P = \frac{m[u,v_P]}{u} = m[\eta q]$  and  $\alpha_w^T = \frac{m[u,v_T]}{u} = m[(1-\eta)q]$ , respectively<sup>11</sup>. It is assumed that only unemployed workers search for a job (there is no on-the-job search).

When a worker meets a vacancy, there is a match-specific productivity. Let  $F_i(x)$  be the invariant worker-firm productivity distribution, for  $i = P, T$ , from which the productivity  $x$  is drawn. Not all meetings create a job because not all workers draw a high enough productivity to make the match worthwhile. Only draws higher than the reservation productivity of new hires under permanent contracts ( $x_{OP}^*$ ) or higher than the reservation productivity under temporary contracts ( $x_T^*$ ) end up with a job creation for each type of contract. Let  $U$  be the value of unemployment,  $W_{OP}(x)$  be the value of employment for a new hire under a permanent contract, and  $W_T(x)$  be the value of employment for a worker hired under a temporary contract. Therefore, the flow value of unemployment is expressed as:

$$rU = b + \alpha_w^P \int_{x_{OP}^*}^{\infty} \{W_{OP}(x) - U\} f_P(x) dx + \alpha_w^T \int_{x_T^*}^{\infty} \{W_T(x) - U\} f_T(x) dx \quad (2.1)$$

While unemployed, individuals receive a utility (or disutility)  $b$  interpreted as the flow income, which is equivalent to the value of leisure. At rate  $\alpha_w^P$ , a worker meets a vacancy with a permanent contract, and if a job is created there is a capital gain of  $W_{OP}(x) - U$ . Similarly, a worker meets a vacancy with a temporary contract, at rate  $\alpha_w^T$ , and when the job opportunity is taken there is a capital gain of  $W_T(x) - U$ .

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<sup>11</sup>In an analogous way, the rates at which vacancies meet workers for both types of contracts can be stated as:  $\alpha_e^P = \frac{m[\eta q]}{\eta q}$  and  $\alpha_e^T = \frac{m[(1-\eta)q]}{(1-\eta)q}$ . Alternatively:  $\alpha_w^P = \eta q \alpha_e^P$  and  $\alpha_w^T = (1-\eta)q \alpha_e^T$ .

In order to write the flow value of employment under a permanent contract, and according to the previous discussion about the effect of firing costs on wages, it is necessary to distinguish between a new hire (outsider) and a continuing employee (insider), both under permanent contracts. Let  $W_{IP}(x)$  and  $x_{IP}^*$  be the value of employment and the reservation productivity for a continuing employee under a permanent contract, respectively. The flow value of an outsider worker with a permanent contract and current productivity  $x$  can then be written as:

$$rW_{OP}(x) = w_{OP}(x)(1 - \tau_P) + \lambda_P \int_{x_{IP}^*}^{\infty} W_{IP}(x') f_P(x') dx' + \lambda_P F_P(x_{IP}^*) U - \lambda_P W_{OP}(x) \quad (2.2)$$

while the flow value of an insider worker with a permanent contract can be expressed as:

$$rW_{IP}(x) = w_{IP}(x)(1 - \tau_P) + \lambda_P \int_{x_{IP}^*}^{\infty} W_{IP}(x') f_P(x') dx' + \lambda_P F_P(x_{IP}^*) U - \lambda_P W_{IP}(x) \quad (2.3)$$

An outsider worker with a permanent contract in a job with productivity  $x$  receives an after payroll tax wage rate of  $w_{OP}(x)(1 - \tau_P)$ . A productivity shock arrives at a Poisson rate  $\lambda_P$ . If the new productivity  $x'$  is above the reservation productivity  $x_{IP}^*$ , then the worker remains employed, but he is now an insider worker with a capital gain or loss of  $W_{IP}(x') - W_{OP}(x)$ . There is the possibility of productivity gains if  $x' > x$ . On the contrary, if the new productivity is below the reservation productivity, then the worker becomes unemployed and the capital loss is  $U - W_{OP}(x)$ . If an insider worker with a permanent contract continues as an employee, then he receives an after-payroll-tax wage rate of  $w_{IP}(x)(1 - \tau_P)$  and a capital gain or loss of  $W_{IP}(x') - W_{IP}(x)$ ; but if the job is terminated, then the capital loss for the worker is  $U - W_{IP}(x)$ .

When a worker is employed with a temporary contract the flow value is:

$$rW_T(x) = w_T(x)(1 - \tau_T) + \lambda_T U - \lambda_T W_T(x) \quad (2.4)$$

In this case, a worker with a temporary contract and productivity  $x$ , receives an after-payroll-tax wage rate of  $w_T(x)(1 - \tau_T)$ . He loses his job at a Poisson rate  $\lambda_T$  with a consequent capital loss of  $U - W_T(x)$ . Note that this reflects the fact that temporary contracts are not converted into permanent contracts upon their expiration dates.

### 2.2.2 FIRMS' VALUE FUNCTIONS

$J_{OP}(x)$  and  $J_{IP}(x)$  are defined as the values of a filled job for a new hire (outsider) and a continuing employee (insider), both under permanent contracts, respectively. Similarly,  $J_T(x)$  is defined as the value of a filled job under a temporary contract. Also, let  $V_P$  and  $V_T$  be the values of creating a vacancy for each type of contract, permanent and temporary, respectively. Using these definitions the flow values of a filled job under a permanent contract can be written as:

$$\begin{aligned} rJ_{OP}(x) &= x - w_{OP}(x)(1 + \phi_P) + \lambda_P F_P(x_{IP}^*) (V_P - J_{OP}(x) - \Psi) \\ &\quad + \lambda_P \int_{x_{IP}^*}^{\infty} \{J_{IP}(x') - J_{OP}(x)\} f_P(x') dx' \end{aligned} \quad (2.5)$$

and

$$\begin{aligned} rJ_{IP}(x) &= x - w_{IP}(x)(1 + \phi_P) + \lambda_P F_P(x_{IP}^*) (V_P - J_{IP}(x) - \Psi) \\ &\quad + \lambda_P \int_{x_{IP}^*}^{\infty} \{J_{IP}(x') - J_{IP}(x)\} f_P(x') dx' \end{aligned} \quad (2.6)$$

Firms using permanent contracts receive a flow output of  $x$  and pay an after payroll tax wage rate of  $w_{OP}(x)(1 + \phi_P)$  if a worker is an outsider, and  $w_{IP}(x)(1 + \phi_P)$  if he is an insider. In this setup, both the employer and the employee pay payroll taxes, making it possible to differentiate the source of the tax payment. There are two possible outcomes when there is a productivity shock. First, for any productivity greater than the reservation productivity the firm continues producing and the capital gains or losses are  $J_{IP}(x') - J_{OP}(x)$  and  $J_{IP}(x') - J_{IP}(x)$  for an outsider and an insider worker,

respectively. Second, if the shock is sufficiently bad, that is, the new productivity has fallen below the reservation productivity, then the worker is dismissed and the firm has to pay the severance tax ( $\Psi$ ). In this case, the capital loss,  $V_P - J_i(x) - \Psi$  for  $i = IP, OP$ , takes into account that the firm now has an unfilled vacancy and has to pay the severance tax.

In turn, the flow value of a filled job under a temporary contract is:

$$rJ_T(x) = x - w_T(x)(1 + \phi_T) + \lambda_T (V_T - J_T(x)) \quad (2.7)$$

Firms using temporary contracts receive a flow output of  $x$  and pay an after payroll tax wage rate of  $w_T(x)(1 + \phi_T)$ . It is assumed that the payroll taxes differ with the types of contracts. When there is a termination shock the match is destroyed at no cost, generating a capital loss of  $V_T - J_T(x)$  to the firm. Thus, both the worker and the firm once again engage in the search process.

Finally, the flow values of unfilled vacancies for both types of contracts are:

$$rV_P = -k_P + \alpha_e^P \int_{x_{OP}^*}^{\infty} \{J_{OP}(x) - V_P\} f_P(x) dx \quad (2.8)$$

$$rV_T = -k_T + \alpha_e^T \int_{x_T^*}^{\infty} \{J_T(x) - V_T\} f_T(x) dx \quad (2.9)$$

For firms to keep the vacancies while searching, they pay a per-period fixed cost of  $k_P$  and  $k_T$ , according to the type of contract, permanent and temporary, respectively. At rate  $\alpha_e^P = \frac{\alpha_w^P}{\eta q}$ , firms with a permanent contract job meet workers, and if the realized match-specific productivity is good enough (greater than the reservation productivity  $x_{OP}^*$  of a new hire with this type of contract), then the vacancy is filled and the firms have a capital gain of  $J_{OP}(x) - V_P$ . In the case of firms with a temporary contract job, meetings occur at rate  $\alpha_e^T = \frac{\alpha_w^T}{(1-\eta)q}$  and the capital gain for the firms is  $J_T(x) - V_T$  if the job is created.



### 2.2.3 STEADY-STATE EQUILIBRIUM

The steady-state condition requires that both: (1) the flow out of unemployment into jobs with permanent contracts is equal to the flow into unemployment from permanent contract jobs:

$$\alpha_w^P [1 - F_P(x_{OP}^*)] u = \lambda_P F_P(x_{IP}^*) e_P$$

and (2) the flow out of unemployment into jobs with temporary contracts is equal to the reverse flow:

$$\alpha_w^T [1 - F_T(x_T^*)] u = \lambda_T (1 - u - e_P)$$

Combining the last two equations and using the fact that  $e_P + e_T + u = 1$  makes it possible to find expressions for the unemployment rate (the Beveridge curve) and the employment rates in temporary and permanent contract jobs:

$$u = \frac{\lambda_T \lambda_P F_P(x_{IP}^*)}{\alpha_w^P [1 - F_P(x_{OP}^*)] \lambda_T + \alpha_w^T [1 - F_T(x_T^*)] \lambda_P F_P(x_{IP}^*) + \lambda_T \lambda_P F_P(x_{IP}^*)} \quad (2.10)$$

$$e_P = \frac{\lambda_T \alpha_w^P [1 - F_P(x_{OP}^*)]}{\alpha_w^P [1 - F_P(x_{OP}^*)] \lambda_T + \alpha_w^T [1 - F_T(x_T^*)] \lambda_P F_P(x_{IP}^*) + \lambda_T \lambda_P F_P(x_{IP}^*)} \quad (2.11)$$

$$e_T = \frac{\alpha_w^T [1 - F_T(x_T^*)] \lambda_P F_P(x_{IP}^*)}{\alpha_w^P [1 - F_P(x_{OP}^*)] \lambda_T + \alpha_w^T [1 - F_T(x_T^*)] \lambda_P F_P(x_{IP}^*) + \lambda_T \lambda_P F_P(x_{IP}^*)} \quad (2.12)$$

The next step in finding the equilibrium is defining how wages are determined. Since workers and employers meet on a bilateral basis, wages are determined in a bargaining process between both parties once the match-specific productivity is realized. As is a common practice in the literature, the generalized axiomatic Nash bilateral bargaining outcome is used to determine wages [Mortensen and Pissarides, 1999a]. If  $\beta_P$  and  $\beta_T$  are the worker's relative bargaining power parameters when he faces an employer offering a permanent and a temporary contract, respectively, the different wage rates solve the following optimization problems (according to the type of

contract and if the worker is an outsider or an insider)<sup>12</sup>:

$$\begin{aligned} & \max_{\{w_{OP}(x)\}} (W_{OP}(x) - U)^{\beta_P} (J_{OP}(x) - V_P)^{1-\beta_P} \\ & \max_{\{w_{IP}(x)\}} (W_{IP}(x) - U)^{\beta_P} (J_{IP}(x) - V_P + \Psi)^{1-\beta_P} \\ & \max_{\{w_T(x)\}} (W_T(x) - U)^{\beta_T} (J_T(x) - V_T)^{1-\beta_T} \end{aligned}$$

From the worker's point of view, the threat point is simply the value of breaking the contract, which is the value of unemployment. From the firm's point of view, the threat point is the value of continued search, and it differs depending on the type of contract and whether the worker is an outsider or an insider. If an unemployed worker meets a firm with a permanent contract (the worker becomes a new hire or an outsider if the job is formed), then the threat point in the bargaining process is the value of an unfilled vacancy ( $V_P$ ) since the firm does not have to pay the severance tax if the worker is not hired. On the other hand, if a firm is bargaining the wage with a continuing permanent contract employee (an insider), then the threat point is  $V_P - \Psi$  because if the worker is dismissed the firm ends up with an unfilled vacancy and the obligation to pay the severance tax. Finally, if an unemployed worker meets a firm with a temporary contract, the threat point is simply the value of an unfilled vacancy for this type of contract ( $V_T$ ). The total surplus from a match for  $i = OP, IP, T$  ( $S_i(x)$ ) is defined as the sum of the values to the firm and the worker net of their values of continued search and payroll taxes. Therefore:

$$\begin{aligned} S_{OP}(x) &= (W_{OP}(x) - U) + \frac{(1 - \tau_P)}{(1 + \phi_P)} (J_{OP}(x) - V_P) \\ S_{IP}(x) &= (W_{IP}(x) - U) + \frac{(1 - \tau_P)}{(1 + \phi_P)} (J_{IP}(x) - V_P + \Psi) \\ S_T(x) &= (W_T(x) - U) + \frac{(1 - \tau_T)}{(1 + \phi_T)} (J_T(x) - V_T) \end{aligned}$$

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<sup>12</sup>Wages are bargained when an unemployed worker meets a firm (outsider permanent or temporary) and when a shock arrives (insider permanent).

The solutions of the above optimization problems split the total surplus in fixed proportions at all points in time and at all  $x \geq x_i^*$  for  $i = OP, IP, T$ . In each case, the proportions of the total surplus that goes to the workers are:

$$\begin{aligned} W_{OP}(x) - U &= \beta_P S_{OP}(x) \\ W_{IP}(x) - U &= \beta_P S_{IP}(x) \\ W_T(x) - U &= \beta_T S_T(x) \end{aligned} \tag{2.13}$$

while the firms obtain:

$$\begin{aligned} J_{OP}(x) - V_P &= (1 - \beta_P) \frac{(1 + \phi_P)}{(1 - \tau_P)} S_{OP}(x) \\ J_{IP}(x) - V_P + \Psi &= (1 - \beta_P) \frac{(1 + \phi_P)}{(1 - \tau_P)} S_{IP}(x) \\ J_T(x) - V_P &= (1 - \beta_T) \frac{(1 + \phi_T)}{(1 - \tau_T)} S_T(x) \end{aligned} \tag{2.14}$$

Using equations (2.13) and (2.14) to rewrite the flow values of workers and firms, equations (2.1) to (2.7), in terms of the total surplus,<sup>13</sup> and making the appropriate substitutions, it is easy to show that the wage equations are:

$$w_{OP}(x) = \frac{\beta_P (x - \lambda_P \Psi) + (1 - \beta_P) \frac{(1 + \phi_P)}{(1 - \tau_P)} rU}{(1 + \phi_P)} \tag{2.15}$$

$$w_{IP}(x) = \frac{\beta_P (x + r\Psi) + (1 - \beta_P) \frac{(1 + \phi_P)}{(1 - \tau_P)} rU}{(1 + \phi_P)} \tag{2.16}$$

$$w_T(x) = \frac{\beta_T x + (1 - \beta_T) \frac{(1 + \phi_T)}{(1 - \tau_T)} rU}{(1 + \phi_T)} \tag{2.17}$$

These wage equations are very similar to those found by Albrecht et al. [2009]. The only difference is that, in this chapter, workers also pay payroll taxes. In all cases, the wage is a weighted average of the match-specific productivity (adjusted by the severance tax in the case of permanent workers) and the worker's continuation value.

<sup>13</sup>The flow value equations written in terms of the total surplus are shown in Appendix A.1.

Since  $w_{OP}(x) = w_{IP}(x) - \frac{\beta_P(\lambda_P+r)}{(1+\phi_P)}\Psi$  and given that  $(r, \lambda_P, \beta_P, \Psi)$  are all positive and  $0 \leq \phi_P \leq 1$ , the wage of a continuing employee (insider) with a permanent contract is higher than that earned by a new hire (outsider) with a similar type of contract (that is,  $w_{IP}(x) > w_{OP}(x)$ ). This reflects the fact that a continuing employee has a better bargaining position with respect to the firm than a new hire because of the severance tax<sup>14</sup>.

Once again, using the workers' and firms' flow values written in terms of the total surpluses it is straightforward to verify that:

$$\begin{aligned} S_{OP}(x) &= \frac{x - x_{OP}^* (1 - \tau_P)}{r + \lambda_P (1 + \phi_P)} \\ S_{IP}(x) &= \frac{x - x_{IP}^* (1 - \tau_P)}{r + \lambda_P (1 + \phi_P)} \\ S_T(x) &= \frac{x - x_T^* (1 - \tau_T)}{r + \lambda_T (1 + \phi_T)} \end{aligned} \quad (2.18)$$

At this point, a discussion on the optimality of the match formation decision rule, which has a reservation value property, is necessary. So far it is assumed that in the model this decision rule is optimal. It is evident from equations (2.18) and (2.13), that both the total surplus function and the value of employment are strictly increasing in productivity  $x$ . Since the value of unemployment is constant, there is a reservation productivity  $x_i^*$  such that  $W_i(x) = U$ , for  $i = OP, IP, T$ . Moreover, at that productivity the total surplus is zero ( $S(x_i^*) = 0$ )<sup>15</sup>. Using the flow values for an insider worker with a permanent contract, the wage equation, the total surplus definitions, and the condition  $S(x_{IP}^*) = 0$ , it is possible to verify that:

$$x_{IP}^* = \frac{(1 + \phi_P)}{(1 - \tau_P)} rU - r\Psi - \frac{\lambda_P}{r + \lambda_P} \int_{x_{IP}^*}^{\infty} (x' - x_{IP}^*) f_P(x') dx' \quad (2.19)$$

<sup>14</sup>For a detailed discussion see Pissarides [2000], chapter 9.

<sup>15</sup>In the case of the permanent contracts, for which the termination is endogenous, this reservation productivity is also the destruction threshold.

Define  $T(x_{IP}^*)$  equal to the left hand side of equation (2.19). Note that  $T : \mathbb{R} \rightarrow \mathbb{R}$  and that it is differentiable. The function  $T(x_{IP}^*)$  is a contraction on  $\mathbb{R}$  with respect to the usual metric if there is a real number  $\pi \leq 1$  such that the derivative  $|T'(x_{IP}^*)| < \pi$  for all  $x_{IP}^* \in \mathbb{R}$ . Note that  $T'(x_{IP}^*) = \frac{\lambda_P}{r+\lambda_P}(1-F_P(x_{IP}^*)) < \pi \leq 1$  if  $r+\lambda_P F_P(x_{IP}^*) > 0$ , which is true given the possible values of the model parameters. The direct application of the contraction mapping theorem implies that the equation  $x_{IP}^* = T(x_{IP}^*)$  has a unique solution in  $\mathbb{R}$ <sup>16</sup>.

In the same way, the flow value of an outsider permanent worker, the wage equation, the definition of total surplus, and the condition  $S(x_{OP}^*) = 0$  can be used to find an expression for the reservation productivity of this type of worker. Additionally, equation (2.19) can assist in writing the resulting expression as:

$$x_{OP}^* = x_{IP}^* + (\lambda_P + r) \Psi \quad (2.20)$$

Note that  $x_{OP}^* \geq x_{IP}^*$ , which once again reflects the better bargaining position of the insider worker. Also, since  $x_{IP}^*$  is uniquely determined, so is  $x_{OP}^*$ . Finally, the flow values of temporary contracts and the wage equation, together with the definition of the total surplus and the condition  $S(x_T^*) = 0$ , generate:

$$x_T^* = \frac{(1 + \phi_T)}{(1 - \tau_T)} rU \quad (2.21)$$

The reservation productivity for a temporary contract is equal to the flow value of the unemployment state (adjusted for payroll taxes), which is the usual result when the model has exogenous destruction and when there is no severance tax.

To close the model, the free-entry condition in the vacancy creation problem for both types of contracts is used. Profit maximization requires that all rents from new job creations should be exhausted such that the value of one more vacancy is zero,

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<sup>16</sup>Note that the solution is unique given that the value of  $rU$  is a function of the endogenous variables  $q$  and  $\eta$  (as mentioned in the next subsection)

that is  $V_i = 0$  for  $i = OP, T$  [Mortensen and Pissarides, 1994]. Applying this condition to equations (2.8) and (2.9) and the definitions of total surplus in equation (2.18), the following equations can be obtained:

$$k_P = \frac{m[\eta q](1 - \beta_P)}{\eta q (r + \lambda_P)} \int_{x_{OP}^*}^{\infty} (x - x_{OP}^*) f_P(x) dx \quad (2.22)$$

$$k_T = \frac{m[(1 - \eta) q](1 - \beta_T)}{(1 - \eta) q (r + \lambda_T)} \int_{x_T^*}^{\infty} (x - x_T^*) f_T(x) dx \quad (2.23)$$

which implicitly defines a system of equations in  $q$  and  $\eta$ . These last two expressions and the definition of the total surplus can be used to rewrite the flow value of unemployment in equation (2.1) in the following way:

$$rU = b + \left( \frac{1 - \tau_P}{1 + \phi_P} \right) \frac{\eta q \beta_P k_P}{(1 - \beta_P)} + \left( \frac{1 - \tau_T}{1 + \phi_T} \right) \frac{(1 - \eta) q \beta_T k_T}{(1 - \beta_T)} \quad (2.24)$$

A formal definition of the *steady-state equilibrium* can now be stated<sup>17</sup>:

**Definition 2.2.1** *Given a vector of parameters  $(b, \lambda_P, \lambda_T, r, \beta_P, \beta_T, k_P, k_T)$ , a matching function  $m(\cdot)$ , a vector of taxes  $(\tau_P, \tau_T, \phi_P, \phi_T, \Psi)$ , and probability distribution functions for the productivity of permanent and temporary contracts  $F_P(x)$  and  $F_T(x)$ , a steady-state equilibrium in a dual labor market economy is a labor market tightness  $q$  and a proportion of job vacancies with permanent contracts  $\eta$ , together with reservation productivities  $x_i^*$  for  $i = OP, IP, T$ , unemployment rate  $u$  and employment rates  $e_P$  and  $e_T$  such that:*

1. *Given  $q$  and  $\eta$ , and  $rU$  from equation (2.24), the reservation productivities  $x_i^*$  for  $i = OP, IP, T$  solve equations (2.19) to (2.21).*
2. *Given the reservation productivities  $x_i^*$  for  $i = OP, IP, T$ , the unemployment rate  $u$  and employment rates  $e_P$  and  $e_T$  satisfy equations (2.10) to (2.12).*

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<sup>17</sup>The algorithm to computationally implement the model comes directly from the definition of steady-state equilibrium and is presented in Appendix A.2.

3.  $q$  and  $\eta$  solve the system of equations (2.22) to (2.23) and are consistent with the reservation productivities  $x_i^*$  for  $i = OP, T$ .

The equilibrium exists if the system of equations (2.22) to (2.23) has a solution for  $q$  and  $\eta$  in the third part of Definition 1, which in turn depends entirely on the matching function (recall that  $x_i^*$  for  $i = OP, IP, T$  is given in this stage). Under the assumptions made for the matching function, particularly the one on its increasing characteristic, there is a solution possibly involving a corner solution in  $\eta$ . If, in addition, it is assumed that the matching function is strictly increasing, then that solution is unique.

### 2.3 DATA

To estimate the model, this chapter uses microdata on the Chilean labor market, particularly, the longitudinal Social Protection Survey (Encuesta de Protección Social or EPS) from the Subsecretaría de Previsión Social<sup>18</sup>. This survey, which interviewed persons over the age of 18 years in 2002, 2004, 2006 and 2009, builds a panel of labor histories. In each survey, interviewers explicitly asked about the events (states in the labor market, monthly wages and weekly hours worked in each job) occurring in the years after the last survey in which the individual participated. A feature that makes this survey very attractive is its longitudinal dimension, one that is not commonly found in Latin American countries' datasets. Even though the model to be estimated does not have on-the-job search, which makes the data on labor market histories in the employment state less relevant, the longitudinal dimension provides valuable

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<sup>18</sup>The survey is conducted by the Microdata Center of the Economics Department at the University of Chile with the participation of academics of the University of Pennsylvania and the University of Michigan.

information on transitions from the unemployment state to temporary and permanent contract jobs, which is central for the identification strategy used in the next section.

The estimation of the search model considers only the persons surveyed in 2002, 2004 and 2006<sup>19</sup>. The first step in preparing the data consisted of appending the three surveys. Two problems arose in this process. First, there were overlapping events; events at the end of the 2002 survey overlapped with those at the beginning of the 2004 survey, and events at the end of the 2004 survey overlapped with those at the beginning of the 2006 survey. Two overlapped events were merged if they belonged to the same state and had the same type of contract (for the case of employed workers). Second, there were contained events; events at the end of the 2002 survey were also contained in those at the beginning of the 2004 survey, and events at the end of the 2004 survey were also contained in those at the beginning of the 2006 survey. In this case, the events occurring in the 2002 and 2004 surveys were kept since it is assumed that the data on the events that occurred in the same year as the survey is more accurate. Finally, individuals who presented inconsistencies in their histories, that is, overlapped or contained events with different states (unemployment and employment), were discarded. There were also individuals with missing information on wages, hours worked or event dates. These inconsistencies and missing data represented 18.4% of the sample.

Since the model assumes ex-ante homogeneous workers, some observed heterogeneity controls are necessary to guarantee a certain degree of homogeneity consistent with the model assumptions. In particular, the estimation sample satisfies the following criteria: males, heads of household, between the ages of 25 and 60 years, without a college degree. Initially, there were 4,194 individuals in the sample who had these characteristics (once the inconsistencies were discarded). The literature

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<sup>19</sup>The 2009 survey is contaminated with the recent recession, which started in 2008.



that estimates a search model, without on the job search, usually uses cross-section samples of workers in employment and unemployment states [Eckstein and van den Berg, 2007]. Therefore, following this literature, a cross-section sample comprised of all labor market states (unemployment and employment spells) prevailing in June 2005 was constructed, and the transitions to temporary and permanent contract jobs were recorded for each unemployment event. Only 3,006 of the initial group of persons had spells that continue into 2005.

The sample size was further reduced due to other problems with the data. First, there were double censored spells in the unemployment state, which could not be used because they generate an identification problem as discussed in the next section<sup>20</sup>. Fortunately, this type of spell represented only 7.1% of the valid sample, and could be discarded. Second, the sample contained unrealistically high wages. Therefore, to avoid this outlier problem, 2.5 of the upper and lower percentiles in wages were dropped from the sample (resulting in a reduction of 11.2% of the valid sample observations). This elimination generated an average wage that is comparable with another Chilean Household Survey<sup>21</sup>. Finally, the unemployment state is characterized only by persons, who are looking for a job, because the model does not have data on participation decisions. Hence, the elimination of inactive workers from the sample generates a further decrease of 1.6% and leaves the estimation sample with a total of 2,170 individuals.

Table 2.6 reports descriptive statistics of the sample. In the top panel, hourly wages are measured in U.S. dollars of 2004. They are calculated using reported weekly hours

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<sup>20</sup>There were also very long unemployment spells. The estimations use only unemployment spells with durations less than 50 months. Eliminating some unemployment information does not affect the sample representativity because the proportion of unemployed individuals remains close to that reported in the CASEN 2006 (4%)

<sup>21</sup>CASEN 2006 (Table 2.4).

worked and monthly wages, which are expressed in 2004 prices using the CPI and converted to U.S. dollars using the average exchange rate for that year. In the sample, there are 1,602 workers with permanent contracts and 454 with temporary contracts for whom there is valid information on wages. It is observed that, on average, workers with permanent contracts earn almost 63% more than workers with temporary contracts. Duration in each state, which is presented in the second panel of Table 2.6, is measured in months. The sample contains 114 unemployed individuals, who have been unemployed for 1.4 years, on average<sup>22</sup>.

The right censored unemployment duration spells dominate the left censored ones, but majority of the spells are complete. As expected, permanent jobs last, on average, almost 4 times longer than temporary jobs. In both types of jobs the employment durations show a censoring problem at the beginning of the sample (left) and at the end of the time span (right). In the case of permanent contract jobs, left censored spells do not represent an important proportion of all spells. The third panel of Table 2.6 shows the percentage of unemployment spells that have transitioned from this state to each type of job. From all unemployment spells, there is information on the transitions to permanent and temporary contract jobs for 26 (representing 22.8%) and 70 (representing 61.4%) individuals, respectively. The remaining unemployment spells are right censored for which there is no information regarding transitions. Finally, the

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<sup>22</sup>This average unemployment duration is high when compared to that of the 2006 CASEN survey, in which the average unemployment duration is only 2.7 months. It is well known that one of the most important problems encountered when working with self-reported data is the quality of the information, where short lived events tend to be over reported. The problem is exacerbated when the self-reported data is retrospective as is the case in the EPS. However, given its longitudinal dimension, which is central for the identification of the parameters, this chapter uses the EPS, even though the CASEN has a bigger sample size and is more accurate (it is self-reported, but not retrospective).

bottom panel shows that there is a greater share of permanent job contracts in the sample<sup>23</sup>.

Payroll tax and severance tax parameters are not estimated. Instead, these parameters are obtained from the labor legislation and the existing literature. The payroll taxes can be divided into two groups: social security contributions and unemployment insurance. Income taxes are not included in the value of payroll taxes because jobs under temporary and permanent contracts are formal jobs and pay equal income taxes. Social security contributions comprise 20% of wages (10% goes towards retirement, 7% towards health and approximately 3% towards disability) and are paid entirely by the worker [Edwards and Edwards, 2000]. On the other hand, the unemployment insurance contribution depends on who pays the tax. In particular, workers hired under permanent contracts pay 0.6% of their wages to the unemployment insurance, while employers contribute 1.6% towards this insurance. If a worker is hired under a temporary contract, only the employer contributes 3% of the wages towards unemployment insurance [Fajnzylber et al., 2009].

Finally, the EPS survey contains information on the reasons for job termination and whether a severance payment occurred or not. Therefore, in principle it is possible to calculate the severance payment. However, since information on wages and duration are required<sup>24</sup>, and durations are likely to be (left-) censored, the average firing cost is going to be underestimated. In addition, there are other firing costs that are not considered in the data. Hence, in this chapter the firing cost is expressed in terms of the average wage of permanent contract jobs, that is,  $\Psi = \Gamma \bar{w}$ , where an estimate

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<sup>23</sup>The low percent of temporary contracts underestimates the importance of temporary workers when compared with that of the 2006 CASEN survey (Table 2.6).

<sup>24</sup>If the contract lasts for more than 1 year and the employer dismisses the worker for economic reasons, he must provide the worker with a severance payment of one wage per year of work for up to 11 payments (Código del Trabajo, Gobierno de Chile).

of  $\Gamma$  is obtained from external sources. The World Bank (*Doing Business Project*) estimates a firing cost of 52 weeks for Chile ( $\Gamma \simeq 12$  months)<sup>25</sup>, which is in line with the ones used in the literature for Latin American countries; for example, Bosch and Esteban-Pretel [2012] use a proportion of 15 months of average wages of formal jobs in the case of Brazil.

## 2.4 ESTIMATION

The model is estimated by maximum log-likelihood method using supply side information of the labor market, that is, durations in different labor market states and wages under temporary and permanent contracts. While this information, as pointed out by Flinn [2006], is useful in learning about arrival and termination rates, and the parameters that characterize the productivity distribution, it is not useful in characterizing the vacancy creation problem. Hence, the lack of demand side information is clearly a limitation. Since the market tightness ( $q$ ) and the proportion of vacancies with permanent contracts ( $\eta$ ) affect only the arrival rates  $\alpha_w^P$  and  $\alpha_w^T$ , it is possible to estimate them as parameters, after which  $q$  and  $\eta$  can be recovered by relying on other sources of information or by making specific assumptions regarding the matching function. Consequently, the vacancy cost parameters can also be estimated. This is one of the alternative identification strategies proposed by Flinn [2006] to estimate search and matching models with endogenous arrival rates only with supply side information. The identification of arrival and termination rates and productivity distribution parameters relies on Flinn and Heckman [1982], and since the model differentiates between insider and outsider permanent workers, a feature that is unobserved in the

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<sup>25</sup>This firing cost includes the cost of advanced notice requirements, severance payments, and penalties due when terminating a redundant worker.

data, the estimation also relies on Flabbi [2010a] strategy to identify a mixture of distributions.

#### 2.4.1 THE LIKELIHOOD FUNCTION

The data consists of unemployment durations, hourly wages and durations in jobs with temporary and permanent contracts, and transitions from unemployment to both types of jobs, that is:

$$(\{t_{i,u}, I_i(u \rightarrow e_P), I_i(u \rightarrow e_T)\}_{i \in U}, \{w_{i,P}, t_{i,e_P}\}_{i \in E_P}, \{w_{i,T}, t_{i,e_T}\}_{i \in E_T})$$

To find the unemployment duration contribution to the likelihood function, the hazard rate out of unemployment is defined as:

$$h_u = \alpha_w^P [1 - F(x_{OP}^*)] + \alpha_w^T [1 - F(x_T^*)] \quad (2.25)$$

In other words, the hazard rate is defined as the probability that a job is created once a worker meets an employer with any type of contract (reflected as a productivity drawn from the match greater than the reservation productivity). The hazard rate, conditional on the model, is constant. This implies that the contribution of the unemployment duration is the density of a negative exponential random variable with a coefficient equal to the hazard rate [Flabbi, 2010a]. Given that the unemployment duration is observed only for workers who are currently unemployed, the contribution of unemployment duration has to be weighted by the probability of being unemployed (the unemployment rate):

$$\begin{aligned} f_u(t_{i,u}, i \in U) &= f_u(t_{i,u} | i \in U) \Pr(i \in U) \\ &= h_u \exp(-h_u t_u) u \quad t_u > 0 \end{aligned}$$

Using the idea of multiple-exit duration models of Bover and Gómez [2004], it is possible to distinguish between exits from unemployment to a permanent job and

to a temporary job. Let the indicator variables of exit to permanent and temporary employments be denoted by  $D_P = I(u \rightarrow e_P)$  and  $D_T = I(u \rightarrow e_T)$ , respectively. Then, it is possible to define the following hazard rates:

$$\begin{aligned} h_u^P &= \alpha_w^P [1 - F(x_{OP}^*)] \\ h_u^T &= \alpha_w^T [1 - F(x_T^*)] \end{aligned}$$

such that the hazard rate out of unemployment is  $h_u = h_u^P + h_u^T$ . Therefore, the contribution of unemployment duration to the likelihood function becomes:

$$f_u(t_{i,u}, i \in U) = [h_u^P \exp(-h_u^P t_u)]^{D_P} [h_u^T \exp(-h_u^T t_u)]^{D_T} u \quad t_u > 0 \quad (2.26)$$

There are three features of the data that need to be considered in order to derive the contribution of wages to the likelihood function. First of all, wages are observed in the data, but productivity is not. Secondly, observed wages are accepted wages. Finally, this information is available only for currently employed workers. Therefore, and following Flabbi [2010a], the first step in finding the wages contribution is to map the unconditional wage cumulative distribution from the unconditional productivity cumulative distribution, and construct the truncated version of the density of the former distribution taking into account the optimal decisions of the agent in the model (that is, the wage equations and reservation productivities). The second step is to find the corresponding wage density and weight it by the probability of being employed (the employment rate). The detailed derivation is presented in Appendix A.3. The wages contribution to the likelihood function, conditional on being a newly hired worker (outsider) with a permanent contract, is:

$$g(w_i, i \in E_P | w_i > w_{OP}(x_{OP}^*), OP) = \frac{\frac{(1+\phi_P)}{\beta_P} f_P \left( w_i \frac{(1+\phi_P)}{\beta_P} - \frac{(1-\beta_P)}{\beta_P} \frac{(1+\phi_P)}{(1-\tau_P)} rU + \lambda_P \Psi \right)}{1 - F_P(x_{OP}^*)} e_{OP} \quad (2.27)$$

On the other hand, the wages contribution to the likelihood function, conditional on being a continuing employee (insider) with a permanent contract, is:

$$g(w_i, i \in E_P | w_i > w_{IP}(x_{IP}^*), IP) = \frac{\frac{(1+\phi_P)}{\beta_P} f_P \left( w_i \frac{(1+\phi_P)}{\beta_P} - \frac{(1-\beta_P)}{\beta_P} \frac{(1+\phi_P)}{(1-\tau_P)} rU - r\Psi \right)}{1 - F_P(x_{IP}^*)} e_{IP} \quad (2.28)$$

Equations (2.27) and (2.28) are conditioned on observing wages for new hires and for continuing employees, both under permanent contracts. However, information to identify the type of permanent worker is not available in the data. Therefore, one additional step in the construction of the likelihood contribution of wages is necessary for this type of contract. To remove the condition of whether the worker with a permanent contract is an outsider or an insider (considering that  $w_{IP}(x_{IP}^*) = w_{OP}(x_{OP}^*) = w_P(x_P^*)$ ), the following expression is used:

$$\begin{aligned} g(w_i, i \in E_P | w_i > w_P(x_P^*), P) &= g(w_i, i \in E | w_i > w_P(x_P^*), OP) \Pr(OP) \\ &+ g(w_i, i \in E | w_i > w_P(x_P^*), IP) \Pr(IP) \end{aligned}$$

The probability of being a new hire (outsider) is  $\Pr(OP)$ , and it depends on the duration of the job since the worker remains an outsider if there are no productivity shocks, but the longer the contract lasts the more likely it is for productivity shocks to arrive. Productivity shocks, conditional on the model, are governed by a Poisson process. Therefore,  $\Pr(OP) = \Pr[\text{receive 0 shocks in } t] = \exp(-\lambda_P t_{e_P})$ . Also note that  $\Pr(IP) = 1 - \Pr(OP)$ . Using these probabilities, the last equation becomes:

$$\begin{aligned} g(w_i, i \in E_P | w_i > w_P(x_P^*), P, t_{i,e_P}) &= \quad (2.29) \\ &\left[ \frac{\exp(-\lambda_P t_{i,e_P}) \frac{(1+\phi_P)}{\beta_P} f_P \left( w_i \frac{(1+\phi_P)}{\beta_P} - \frac{(1-\beta_P)}{\beta_P} \frac{(1+\phi_P)}{(1-\tau_P)} rU + \lambda_P \Psi \right)}{1 - G(w_P(x_P^*) | P, OP)} \right. \\ &\left. + \frac{(1 - \exp(-\lambda_P t_{i,e_P})) \frac{(1+\phi_P)}{\beta_P} f_P \left( w_i \frac{(1+\phi_P)}{\beta_P} - \frac{(1-\beta_P)}{\beta_P} \frac{(1+\phi_P)}{(1-\tau_P)} rU - r\Psi \right)}{1 - G(w_P(x_P^*) | P, IP)} \right] e_P \end{aligned}$$

which is a mixture of two truncated distributions with a weight equal to the probability of being an outsider worker. The construction of the likelihood contribution of wages, conditional on being a temporary worker, follows the procedure described above and can be written as:

$$g(w_i, i \in E_T | w_i > w_T(x_T^*), T) = \frac{\frac{(1+\phi_T)}{\beta_T} f_T \left( w_i \frac{(1+\phi_T)}{\beta_T} - \frac{(1-\beta_T)}{\beta_T} \frac{(1+\phi_T)}{(1-\tau_T)} rU \right)}{1 - F_P(x_T^*)} e_T \quad (2.30)$$

Using the densities in equations (2.26), (2.29), and (2.30), the likelihood function is:

$$\begin{aligned} L(\Theta^L; w, t) &= \prod_{i=1}^N [f_u(t_{i,u}, i \in U)]^{u_i} \\ &\quad \times [g(w_i, i \in E_P | w_i > w_P(x_P^*), P, t_{i,e_P})]^{e_{i,P} \times (1-u_i)} \\ &\quad \times [g(w_i, i \in E_T | w_i > w_T(x_T^*), T)]^{(1-e_{i,P}) \times (1-u_i)} \end{aligned} \quad (2.31)$$

where  $\Theta^L$  is the vector of parameters,  $t_{i,u}$ ,  $w_i$ ,  $t_{i,e_P}$  are unemployment duration, wages and employment duration under permanent contracts, respectively,  $u_i = 1$  if unemployed and 0 otherwise, and  $e_{i,P} = 1$  if the individual is employed with a permanent contract and 0 otherwise. Note that the employment duration of a job with a permanent contract indirectly contributes to the likelihood function, through the wage contributions, and that employment duration under temporary contracts does not provide useful information to the likelihood.

The reservation productivities are endogenous variables in the model and in order to choose the vector of parameters  $\Theta^L$ , the likelihood in equation (2.31) has to be maximized subject to the following equilibrium conditions:

$$\begin{aligned} x_{IP}^* &= \frac{(1+\phi_P)}{(1-\tau_P)} rU - r\Psi - \frac{\lambda_P}{r+\lambda_P} \int_{x_{IP}^*}^{\infty} (x' - x_{IP}^*) f_P(x') dx' \\ x_{OP}^* &= x_{IP}^* + (\lambda_P + r) \Psi \\ x_T^* &= \frac{(1+\phi_T)}{(1-\tau_T)} rU \end{aligned}$$



Finally,  $rU$  is also an endogenous variable in the model, but for estimation purposes it is treated as a constant<sup>26</sup>. Therefore,  $b$ , which is the only parameter that does not appear directly in the likelihood, is chosen so that all equilibrium conditions are met as described below.

#### 2.4.2 IDENTIFICATION

The identification strategy has three stages. The first follows Flinn and Heckman [1982] and Flabbi [2010a] and is related to the identification of the parameters in the likelihood function (equation 2.31), which are the job arrival rates  $(\alpha_w^P, \alpha_w^T)$ , the productivity and termination shock arrival rates  $(\lambda_P, \lambda_T)$ , the reservation productivities  $(x_{OP}^*, x_{IP}^*, x_T^*)$ , the flow value of unemployment ( $rU$ ), and the parameters governing the productivity distributions  $(F_P(x), F_T(x))$ .

Following Flinn and Heckman [1982], a necessary condition for the identification of the parameters in the likelihood function is the *recoverability condition* of the productivity distribution. Under this condition, the entire wage distribution, and thereby the productivity distribution, should be uniquely recoverable from a truncated distribution with a known truncation point. On the other hand, according to Flabbi [2010a] the necessary condition to identify a mixture of two truncated distributions, such as the likelihood contribution of permanent workers, discussed in the previous subsection, is that the productivity distribution belongs to a location-scale family. In this chapter, it is assumed that the match-specific productivity in both types of contracts is log-normally distributed with mean  $\mu_x^i$  and standard deviation  $\sigma_x^i$  for  $i = P, T$ , that is:

$$F_i(x) = \Phi \left( \frac{\ln(x) - \mu_x^i}{\sigma_x^i} \right); \quad i = P, T$$

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<sup>26</sup>This is a common practice in the literature, see, for example, Eckstein and van den Berg [2007].

where  $\Phi$  is the standard normal cumulative distribution function. The log-normal distribution meets the recoverability condition [Eckstein and van den Berg, 2007] and belongs to a log location-scale family where  $\mu_x^i$  is the location parameter and  $\sigma_x^i$  is the scale parameter [Flabbi, 2010a, Flinn, 2006].

Given the assumed match-specific productivity distributions, the identification of all the parameters in the likelihood rely on information regarding the transitions from unemployment to both types of jobs, the steady state equilibrium conditions (equations 2.10 to 2.12), the equilibrium conditions that determine reservation productivities (equations 2.19 to 2.21), the differences between wage distributions of permanent and temporary contract jobs (their location and scale parameters), and the differences between the wage distributions of permanent contract jobs with different tenures (their location and scale parameters). In the case of the Chilean labor market, Figures 2.2 and 2.3 show that the differences, by type of contract and by tenure, are important and can be exploited in the estimation. Appendix A.4 shows a formal proof that describes this identification strategy.

Two parameters of the model,  $\beta$  and  $r$ , are not estimated but are set exogenously. As pointed out by Eckstein and Wolpin [1995] and Flinn [2006] the Nash bargaining coefficient  $\beta$  is difficult to identify without demand side information. This chapter does not attempt to identify this parameter, instead it is assumed that  $\beta_P = \beta_T = \beta = 0.5$ . The equal bargaining power assumption between workers with permanent and temporary contracts,  $\beta_P = \beta_T$ , can be justified by the non discrimination principle mentioned in Cahuc and Postel-Vinay [2002]; and  $\beta = 0.5$ , which is the common solution in the applied literature, arises when the discount rate is the same for workers and firms (Binmore et al., 1986; Binmore, 1978)<sup>27</sup>. On the other hand, although  $r$  enters the likelihood function directly and not only through  $rU$ , it is not possible to

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<sup>27</sup>Cited in Flabbi [2010a].

identify all other parameters if this parameter is included in the estimation. Therefore, as is frequently done in applied micro-studies,  $r$  is also set exogenously [Eckstein and van den Berg, 2007]. In the particular case of Chile,  $r$  is defined as  $0.0053^{28}$ .

The second stage follows Flinn [2006] and is related to the identification of the demand side parameters, which in the case of this model consists of the matching function,  $m(\cdot)$ , and the cost of posting vacancies,  $(k_P, k_T)$ . Without directly available information about vacancies,  $v_P$  and  $v_T$ , any additional parameters in the matching function  $m(\cdot)$  cannot be identified. This is an important result since knowledge of the  $m(\cdot)$  function is sufficient to identify the cost of the vacancy parameters,  $k_P$  and  $k_T$ .

There are two alternative ways to identify the matching function. One relies on specific assumptions on its functional form and the other relies on the value of any additional parameters in the function. The first, proposed by Flinn [2006], consists in using a matching function that does not contain any unknown parameters. A good option, which fulfills the assumptions made in section 2.2, is the exponential matching function  $m(u, v) = v(1 - e^{-u/v})^{29}$ . The second consists in using external sources to obtain estimates of a Cobb-Douglas matching function parameter<sup>30</sup>. For the case of the Chilean labor market, Belani et al. [2002] estimate the matching function as  $m(u, v) = u^{0.15}v^{0.85}$ . An alternative approach could be to apply the Hosios [1990] condition, that is, to use  $m(u, v) = u^{1-\beta}v^\beta$ . In any case, once the matching function is identified, all demand side parameters are identified.

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<sup>28</sup>This rate represents 6.5% in annualized terms [see, for example, Fuenzalida and Mongrut, 2010].

<sup>29</sup>This matching function can be justified by the presence of coordination failures in the labor market. However, despite its theoretical justification, this matching function generates implausible level and duration of unemployment for which it is, empirically, not a good approximation [Petrongolo and Pissarides, 2001].

<sup>30</sup>This alternative is attractive because the Cobb-Douglas matching function with constant returns to scale has had empirical success [Petrongolo and Pissarides, 2001]. The drawbacks are the lack of micro-foundation of this matching function and the use of external estimates.

Identification and (consistent) estimation of the parameters  $q, \eta, k_P, k_T$  and  $b$  build on the consistent estimators of the parameters  $\alpha_w^P, \alpha_w^T, x_{OP}^*, \lambda_P, \lambda_T, r, x_{IP}^*, x_{IT}^*$  in the following way. First,  $\eta$  and  $q$  solve  $\widehat{\alpha}_w^P = m[\eta q]$  and  $\widehat{\alpha}_w^T = m[(1 - \eta)q]$  provided that the matching function  $m(\cdot)$  is identified. Second  $k_P$  and  $k_T$  solve:

$$\begin{aligned} k_P &= \frac{m[\widehat{\eta}\widehat{q}](1 - \beta_P)}{\widehat{\eta}\widehat{q}(r + \widehat{\lambda}_P)} \int_{\widehat{x}_{OP}^*}^{\infty} (x - \widehat{x}_{OP}^*) f_P(x) dx \\ k_T &= \frac{m[(1 - \widehat{\eta})\widehat{q}](1 - \beta_T)}{(1 - \widehat{\eta})\widehat{q}(r + \widehat{\lambda}_T)} \int_{\widehat{x}_{IT}^*}^{\infty} (x - \widehat{x}_{IT}^*) f_T(x) dx \end{aligned}$$

Finally, once all the above parameters are identified,  $b$  can be recovered using the equilibrium condition:

$$b = r\widehat{U} - \left( \frac{1 - \tau_P}{1 + \phi_P} \right) \frac{\widehat{\eta}\widehat{q}\beta_P\widehat{k}_P}{(1 - \beta_P)} - \left( \frac{1 - \tau_T}{1 + \phi_T} \right) \frac{(1 - \widehat{\eta})\widehat{q}\beta_T\widehat{k}_T}{(1 - \beta_T)}$$

### 2.4.3 ECONOMETRIC ISSUES

Three econometric issues arise in estimating the model: (1) measurement error in wages, (2) censoring in unemployment duration data, and (3) censoring in employment duration data. This subsection explains how each of these issues are dealt with.

Measurement error in wages is incorporated in the estimation procedure for two reasons. First, it is very likely that wages are measured with error since the wage data is self reported and it includes wages from past years <sup>31</sup>. Second, and most important, it is not possible to estimate the reservation productivities using the lowest observed wage in both types of contracts, in the spirit of Flinn and Heckman [1982], because the mapping between the reservation productivity and the reservation wage, in the case of permanent jobs, depends on other parameters to be estimated (the relations are implied in the equilibrium conditions). This problem is critical because the reservation productivities are the truncation parameters in the accepted wage

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<sup>31</sup>As is common in the literature, it is assumed that measurement error is present in wages data but not in duration data [Eckstein and van den Berg, 2007, Flinn, 2006].

distributions. Therefore, changing these parameters in the maximization process of the likelihood function changes its support, which violates one of the regularity conditions<sup>32</sup>. A way to avoid this problem is to introduce measurement error. Following Flinn [2002a] and Flabbi and Leonardi [2010], it is assumed that the measurement error is multiplicative:

$$w^o = w \cdot \varepsilon$$

and log-normally distributed, therefore:

$$m(\varepsilon) = \phi\left(\frac{\ln(\varepsilon) - \mu_\varepsilon}{\sigma_\varepsilon}\right) \frac{1}{\varepsilon\sigma_\varepsilon} \quad \varepsilon > 0$$

In order to restrict the number of parameters to estimate, it is assumed that the conditional expectation of the observed wages is equal to the true wages, as is done in Flinn [2002a]; that is,  $E[w^o|w] = w$ , which implies that  $E[\varepsilon|w] = 1$ . This assumption together with the log-normality assumption implies that the parameters  $\mu_\varepsilon$  and  $\sigma_\varepsilon$  satisfy  $\sigma_\varepsilon = \sqrt{-2\mu_\varepsilon}$ . Therefore, only one parameter of the measurement error distribution has to be estimated.

Given the wage density functions for jobs with permanent and temporary contracts,  $g(w_i, i \in E_P|w_i > w_P(x_P^*), P)$  and  $g(w_i, i \in E_T|w_i > w_T(x_T^*), T)$ , respectively, and the error density function  $m(\varepsilon)$ , the implied density functions of observed wages can be written as:

$$\begin{aligned} g_{w^o}^P(w_i^o) &= \int_{w_P(x_P^*)} \frac{1}{w_i} m\left(\frac{w_i^o}{w_i}\right) g(w_i, i \in E_P|w_i > w_P(x_P^*), P) dw_i \\ g_{w^o}^T(w_i^o) &= \int_{w_T(x_T^*)} \frac{1}{w_i} m\left(\frac{w_i^o}{w_i}\right) g(w_i, i \in E_T|w_i > w_T(x_T^*), T) dw_i \end{aligned}$$

Censoring in unemployment duration data is potentially very problematic because it can generate identification problems and bias the estimated parameters. In particular, if the unemployment spells are double censored, that is right and left censored

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<sup>32</sup>See Flinn and Heckman [1982] for a complete discussion.

at the same time, the identification of the parameters in the likelihood estimation is not possible because permanent unemployment can be generated by a different combination of the parameters [Flinn, 2002a]. For this reason, double censored spells are not used in the estimation. The estimated parameters will be biased when there are right or left censored spells. Fortunately, controlling for these two types of censoring is straightforward when the spells are exponentially distributed, and can easily be incorporated in the likelihood function. Let  $c_i^l$  and  $c_i^r$  be indicator variables taking the value of 1 if the unemployment spell is left and right censored, respectively, and zero otherwise. The likelihood contribution of a complete unemployment spell is

$$f_u(t_{i,u}, i \in U, c_i^l = 0, c_i^r = 0) = h_u \exp(-h_u t_u) u \quad t_u > 0$$

while the likelihood contribution of left and right censored unemployment spells are:

$$f_u(t_{i,u}, i \in U, c_i^l = 1) = \Pr[T \leq t_u] = [1 - \exp(-h_u t_u)] u \quad t_u > 0$$

$$f_u(t_{i,u}, i \in U, c_i^r = 1) = \Pr[T > t_u] = \exp(-h_u t_u) u \quad t_u > 0$$

Taking into account measurement error in wages and censoring in unemployment spells, the likelihood function becomes:

$$\begin{aligned} L(\Theta^L; w, t) &= \prod_{i=1}^N [f_u(t_{i,u}, i \in U, c_i^l = 0, c_i^r = 0)]^{u \times (1-c_i^l) \times (1-c_i^r)} \\ &\quad \times [f_u(t_{i,u}, i \in U, c_i^l = 1)]^{u \times c_i^l \times (1-c_i^r)} \\ &\quad \times [f_u(t_{i,u}, i \in U, c_i^r = 1)]^{u \times (1-c_i^l) \times c_i^r} \\ &\quad \times \left[ \int_{w_P(x_P^*)}^{\frac{1}{w_i} m \left( \frac{w_i^o}{w_i} \right)} g(w_i, i \in E_P | w_i > w_P(x_P^*), P) dw_i \right]^{e_P \times (1-u)} \\ &\quad \times \left[ \int_{w_T(x_T^*)}^{\frac{1}{w_i} m \left( \frac{w_i^o}{w_i} \right)} g(w_i, i \in E_T | w_i > w_T(x_T^*), T) dw_i \right]^{(1-e_P) \times (1-u)} \end{aligned}$$

which is maximized to choose  $\Theta^L$ , subject to equilibrium constraints:

$$\begin{aligned} x_{IP}^* &= \frac{(1 + \phi_P)}{(1 - \tau_P)} rU - r\Psi - \frac{\lambda_P}{r + \lambda_P} \int_{x_{IP}^*}^{\infty} (x' - x_{IP}^*) f_P(x') dx' \\ x_{OP}^* &= x_{IP}^* + (\lambda_P + r) \Psi \\ x_T^* &= \frac{(1 + \phi_T)}{(1 - \tau_T)} rU \end{aligned}$$

The last econometric issue is related to the censoring problem in the employment duration data. In this chapter, only employment spells of jobs with permanent contracts are relevant. Recall that employment duration indirectly contributes to the likelihood function through the wage contribution, because it affects the probability of being an outsider (that is,  $\Pr(OP) = \Pr[\text{receive 0 shocks in } t] = \exp(-\lambda_P t_{e_P})$ ). As previously mentioned, employment duration spells can be left or right censored. Right censored spells do not represent a problem because the probability of receiving a determined number of shocks before time  $t$  is what is important in the model; hence, at that time the future is irrelevant. On the other hand, left censored spells do represent a potential problem. This can be observed by expressing the  $\Pr[\text{receive 0 shocks in } t]$  such that the distinction is made between the observed duration  $t_{e_P}^o$  and the true duration  $t_{e_P}$ . Since  $t_{e_P}^o = t_{e_P} - a$ , where  $a \geq 0$ , then:

$$\begin{aligned} \Pr(OP) &= \exp(-\lambda_P (t_{e_P}^o + a)) \\ &= \exp(-\lambda_P t_{e_P}^o) \exp(-\lambda_P a) \end{aligned}$$

Given that  $\exp(-\lambda_P a) \leq 1$  with  $\lambda_P \geq 0$  and  $a \geq 0$ , it is clear that if  $a$  is not taken into account, then the probability of receiving 0 shocks in  $t$  is overestimated. In the case of permanent contracts, this affects the weights in the mixture of wage densities, which in turn can potentially lead to a bias problem in the estimation.

The censoring problem in the employment duration data is neglected in the estimation results presented in the next subsection since the probability of receiving zero

shocks in  $t$  decreases exponentially with employment duration. Hence, the effect of the additional months in the duration of long spells is not important. This is the case in the data used in the estimations, since the left censored spells duration is at least 17 months (and there are only 2% of these spells).

#### 2.4.4 ESTIMATION RESULTS

Table 2.7 reports the estimation results. The first two rows show the job arrival rates for both temporary and permanent jobs. Temporary jobs arrive more than two times faster than permanent jobs. In particular, while offers with temporary contracts arrive approximately every three months, offers with permanent contracts do so every seven months. Rows five through seven of Table 2.7 report the estimated reservation productivities for permanent (insider and outsider) and temporary jobs. An insider permanent worker and a firm with a permanent contract are willing to continue with a contractual relation if the productivity is at least 1.12 U.S. dollars per hour, which is 20% less than the productivity required to form a match between an outsider permanent worker and a firm with a permanent contract (1.34). This reflects the effect of the firing cost on the bargaining position of an insider worker. When workers going from unemployment to temporary and permanent jobs are compared, results on reservation productivity indicate that workers and firms are less stringent when agreeing on a temporary contract than when forming a permanent contractual agreement. In this case, the difference in the reservation productivity is also 20%. Combining job arrival rates and reservation productivities, the estimation results suggest that workers are, on average, unemployed for a total of 14 months (the hazard rate out of unemployment is 0.074). Table 2.9 reports the predictions of the model for these and other variables.



The productivity shocks arrival rate for permanent jobs, reported in the third row of Table 2.7, indicate that productivity shocks do not occur very often. In fact, this arrival rate, together with the value of the reservation productivity of the insider permanent worker, implies that workers keep their jobs for an average of 65 years. On the other hand, the termination rate for the temporary jobs, reported in the fourth row of Table 2.7, also shows a high persistence in temporary jobs with an average duration of 6 years. In both cases, the hazard rates out of employment are shown in Table 2.9. When comparing these durations with those observed in Table 2.6, it is clear that the shock arrival rate for permanent jobs and the termination rate for temporary jobs are underestimated, as are the correspondent hazard rates out of employment. This is the main drawback of having retrospective self-reported data on unemployment and employment duration. As mentioned in the Data section, this data seems to be over reported compared to another household survey. The model estimation strategy relies heavily on this duration data to estimate the arrival and the termination rates of jobs, as well as the arrival rate of shocks. If the unemployment duration is over reported, then the employment duration needs to be high for it to be consistent with the steady state conditions of the model. This drawback should be kept in mind in the analysis of the implications of the model.

The estimated values for the location and the scale parameters of the log-normal match specific distributions for both types of jobs are shown in the last four rows of Table 2.7. These values imply a substantially lower productivity, on average, for workers in temporary jobs (a difference of 30%). Also, there is nine times more uncertainty at the moment of drawing a productivity from the match specific productivity of a permanent job, than from a match specific productivity of a temporary job. Table 2.9 reports the predictions for the average productivity and its variance and shows that workers receive wage offers that are, on average, 25% higher when they meet firms

with permanent contracts than when they meet firms with temporary ones. Once the job is accepted that difference becomes 60%, on average. Finally, the estimation of all parameters is quite precise when evaluating with the asymptotic standard errors.

Table 2.8 shows the estimated value of the technological parameters (the proportion of permanent vacancies, the market tightness and the flow cost of vacancies in temporary and permanent jobs) and the preference parameter (the flow value of leisure) using both the Cobb-Douglas and the Exponential matching functions. All the results discussed below are conditional on the particular assumptions made about the matching function. First, the proportion of permanent job vacancies in the market is around 25%, regardless of the matching function used. Second, the estimated market tightness differ between matching functions. In particular, the market tightness, along with the unemployment rate in Table 2.9, imply that the total vacancy rate of the economy ( $v_P + v_T$ ) is 1.9% when the Cobb-Douglas function is used, and 2.5% when the Exponential function is used. Third, under the Cobb-Douglas matching function, the flow costs of permanent and temporary jobs are around 45 and 6 U.S. dollars, respectively. Meanwhile, these same flow costs are around 31 and 5 U.S. dollars under the Exponential matching function<sup>33</sup>. In any case, it is clear that maintaining a permanent job vacancy unfilled is substantially (between 6 and 7 times) more expensive than maintaining a temporary job vacancy unfilled. Finally, the flow disutility of leisure is around 4 U.S. dollars per hour and it does not depend on which matching function is used to identify it.

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<sup>33</sup>Comparing this result with that found by Flinn [2002a], who estimates a flow vacancy cost of 128 U.S. dollars for the U.S. economy for 1996, suggests that the cost of an unfilled vacancy of a permanent job is substantially lower in the Chilean labor market. However, the difference is not that significant, relative to the average wage (while in the U.S. economy it is 18 times the average wage, in Chile it is 16 times the average wage).

To conclude this section, some specification tests that were performed and an assessment of the fit of the model are discussed. The last two rows of the bottom panel of Table 2.7 report the statistics of two F-tests. The first test corresponds to the null hypothesis that both types of jobs have the same arrival rate, which implies that the proportion of vacancies is 50% for each type of job. This null hypothesis can be rejected at 1% significance level. Using the asymptotic standard error of the arrival rates in Table 2.7, the hypothesis that the arrival rate of temporary jobs is equal to zero, implying that only permanent jobs survive, and the hypothesis that the arrival rate of permanent jobs is equal to zero, implying that only temporary jobs survive, can also be tested. The results indicate that both hypotheses are also rejected at 1% significance level. Therefore, in the Chilean labor market both types of vacancies, permanent and temporary, coexist but there is one that clearly dominates. The second test tries to verify if the productivity in each type of job is drawn from the same distribution (given that in both cases log-normality is imposed). Once again, the data does not support the hypothesis (at 1% significance level) that productivities in both types of jobs come from the same distribution.

Table 2.9 reports the predictions of the model and some comparable moments in the data. In terms of fit, the wages predicted by the model are slightly higher than its sample counterparts. On the other hand, model predictions of the unemployment and employment rates are really close to those observed in the data. The hazard rate out of unemployment also fits the data well. However, the model predictions of hazard rates out of employment do not fit the data well. This reflects the fact that only unemployment duration data is used in the estimation, making it very sensitive to any data problem.

## 2.5 COUNTERFACTUAL AND POLICY EXPERIMENTS

The counterfactual experiment consists in comparing the benchmark economy, that is, the one characterized by the estimated parameters and in which temporary contracts are allowed, with an economy in which the use of temporary contracts is not allowed by law. In the latter economy, the model is solved assuming  $\eta = 1$  and using all other estimated parameters (except those related with temporary jobs). The policy experiment consists in analyzing the impact of changes in the firing cost on the two economies previously mentioned by taking into account the equilibrium effects. In particular, the experiment analyzes the effect of changes in the firing cost within a range of zero to twice the benchmark severance tax. In performing the counterfactual and policy experiments, a Cobb-Douglas matching function is used to solve the model with Belani et al. [2002] estimate of the elasticity,  $\gamma = 0.85$ . In both exercises, it is possible to analyze the effect, under alternative institutional arrangements of more stringent labor protection, on labor market dynamics (that is market tightness, availability of vacancies of both types of jobs, arrival rates, hazard rates out of unemployment and employment, and unemployment and employment rates) and on productivity and wages (reservation productivities, average offered and accepted wages, and inequality between workers with different types of contracts).

### 2.5.1 LABOR MARKET DYNAMICS

The upper panel of Figure 2.4 shows that at any firing cost, the labor market is tighter when temporary contracts are allowed. In particular, when these contracts are allowed, the market tightness is at least 2.5 times the market tightness when they are not allowed. This is explained by the fact that the presence of temporary contracts increases the vacancies available in the market. Analyzing the effect of an

increase in the firing cost, Figure 2.4 shows that the market tightness decreases with the firing cost when temporary contract jobs are not allowed because this cost makes vacancy creations of permanent jobs less attractive. Quantitatively, the effect is not substantial - going from no firing cost to twice the benchmark firing cost leads to a decrease of 1.2% in the market tightness. On the other hand, when temporary contracts are allowed, the effect of the firing cost on the market tightness is the opposite. Indeed, despite the fact that the firing cost makes permanent job vacancy creations less attractive, they make temporary job vacancy creations more attractive and in the end this latter effect dominates the former one. This is observed in the decreasing proportion of permanent job vacancies shown in the lower panel of Figure 2.4. Market tightness increases by more than 11%, going from no firing cost to twice the benchmark firing cost and the proportion of permanent vacancies decreases by 5 percentage points. Permanent vacancies can disappear if the firing cost is really high (more than 10 times that of the benchmark). This is possible in the model but not plausible in practice.

The arrival rates for permanent and temporary jobs, shown in Figure 2.5, reflect what was discussed above. When temporary jobs are allowed, as the firing cost increases, fewer vacancies for permanent jobs reduce the rate at which they arrive, while more temporary job vacancies accelerate their arrival rate. The reduction in the case of permanent job vacancies is 8.1% and the increase in the case of temporary job vacancies is 16.1%. When temporary jobs are not allowed, the arrival rate of permanent jobs also slows with firing costs but the size of the effect is much smaller - it only reduces permanent job vacancies by 1%.

Figures 2.6 to 2.8 show the effect of firing costs on the different labor market states, that is, on the unemployment and the employment rates, under both types of contracts and their corresponding durations. The upper panel of Figure 2.6 shows

that the unemployment rate falls with more stringent employment protection when temporary contracts are not allowed. This indicates that the effect of the firing cost in reducing the job destruction rate dominates the one that discourages employment creations. The hazard rate out of unemployment, shown in the lower panel of Figure 2.6, decreases suggesting that even though there are fewer unemployed workers, those who are unemployed stay in that state longer. However, the impact on the unemployment rate and its duration is quantitatively small - the unemployment rate only falls by 0.3 percentage points, going from zero protection to twice the benchmark firing cost and the workers stay unemployed only half a month longer. When temporary contracts are allowed, the effect of stringent protection on the unemployment rate is attenuated, indicating that the the effect of the flows out of temporary jobs dominate that of the flows out of unemployment into temporary contracts. The positive impact of temporary jobs is that they help to reduce unemployment duration by one and a half months when employment protection becomes more stringent.

The upper panel of Figure 2.7 shows that the employment rate in permanent jobs increases slightly (by less than one percentage point). This is consistent with the decrease in the unemployment rate when temporary contracts are not allowed. However, the fact that the employment rate of permanent jobs falls by 4 percentage points when temporary contracts are allowed, implying a substitution between permanent and temporary jobs, is more interesting (recall that the unemployment rate is fairly constant in this scenario). The lower panel of Figure 2.7 shows the hazard rate out of permanent jobs. As expected, more stringent protection in permanent jobs discourages its destruction and this is true regardless of whether the use of temporary contracts is allowed or not. Quantitatively, duration of permanent jobs increases by 7 and 11% when temporary contracts are allowed and when they are not, respectively. Finally, the upper panel of Figure 2.8, shows that the employment rate in

temporary jobs increases by 4 percentage points when the firing cost rises. This is consistent with the substitution effect previously mentioned. Figure 2.8, which shows the positive relationship between temporary job shares and employment protection, corresponds to the model counterpart of Figure 2.1. On the other hand, the lower panel of Figure 2.8 shows the hazard rate out of temporary jobs, which is constant by construction (the termination rate in the model is exogenous).

### 2.5.2 PRODUCTIVITY AND WAGES

The upper panel of Figure 2.9 shows how the reservation productivity of new hires with permanent contracts (outsiders) changes with the firing cost. Regardless of the existence of temporary contracts, the firing cost discourages new hires by increasing the threshold at which matches are formed. When temporary contracts are not allowed, this reservation productivity increases by less than 1% with the firing cost, while when both types of contracts coexist it increases by 3.4%. The existence of temporary contracts exacerbates the negative effect on job creations. The middle panel of Figure 2.9 shows the reservation productivity of continuing employees with permanent contracts (insiders). In this case, the reservation productivity decreases with the firing cost and the effect is quantitatively important (it falls by more than 30%). This is explained by the fact that more protection generates a higher bargaining advantage for workers, reducing the firms' outside option. Therefore, firms are willing to maintain a larger proportion of their workers even if they become less productive after a shock has occurred. For both, insiders and outsiders, the reservation productivity is always higher when temporary contracts are allowed, indicating that a higher productivity is sustained with permanent jobs when the two types of contracts coexist. The lower panel of Figure 2.9 shows the reservation productivity of temporary jobs. The positive effect on unemployment of increasing the firing cost in permanent jobs

is that the lower reservation productivity facilitates job creation. The down side is that lower productivity jobs will be created.

Figures 2.10 and 2.11, which were calculated using equations (2.15) to (2.17), show average offered and accepted wages, respectively. The former uses the unconditional expected productivity, while the latter uses the expected productivity conditional on productivities greater than the reservation value. In the case of permanent jobs, the firing cost affects average accepted wages through three mechanisms. First, they directly affect the total surplus of the match. Second, they have an equilibrium effect on the flow value of unemployment. Third, they have an equilibrium effect on the conditional average productivity through the reservation values. Since average offered wages depend on the unconditional expected productivity by definition, the last mechanism does not operate. On the other hand, in the case of temporary jobs, average accepted wages are affected by the equilibrium effects on the flow value of unemployment and the reservation productivity, while average offered wages are only affected by the equilibrium effects on the flow value of unemployment.

In Figure 2.10, it is observed that the direct effect of the firing cost dominates in the case of permanent jobs. The upper panel shows that average offered wages for new hires fall between 6 and 8%, depending on whether temporary contracts are allowed or not, respectively. The middle panel shows that there is an opposite effect in the case of continuing permanent employees, that is, wages increase by approximately 13%. The lower panel shows the average offered wages for temporary contracts. In this case, since permanent job vacancies exist, the average offered wages fall (1.7%), along with the flow value of unemployment. In the upper and middle panels of Figure 2.11, it is shown that average accepted wages follow a different pattern for permanent jobs. This implies that the equilibrium effects of the firing cost on reservation productivities are quite important. Indeed, they almost offset the direct effect of the firing cost for new



hires (the decrease is only between 1 and 3%) and substantially reduce the average accepted wages for continuing employees (between 10 and 14%). The lower panel shows a fall of 2.2% in average accepted wages for temporary jobs. Hence, the effect on the reservation productivity also contributes to this fall. Finally, both average offered and accepted wages are higher when temporary jobs are allowed. This is due to a higher unemployment (there are more permanent job vacancies), in the case of the average offered wages, and a higher reservation productivity, in the case of average accepted wages.

This subsection concludes with the effect of the firing cost on inequality. In this chapter, inequality is defined as the difference in wage rates of permanent and temporary workers. Therefore, in this exercise both types of contracts are allowed. Figure 2.12 shows the ratios between the average wage in temporary jobs and the average wage in permanent jobs for new hires and for continuing employees (the offered wages are in the upper panel, while the accepted wages are in the lower panel). There are three comments worth mentioning from the analysis of Figure 2.12. First, inequality is high since the gaps between offered wages for permanent and temporary workers are 20 and 30% (comparing new hires in temporary jobs and continuing employees in permanent jobs, respectively). The gap is even greater (around 40%) when the focus is on the accepted wages. Second, the pattern of the wage ratios is consistent with the changes in wages given by changes in the firing cost. In particular, inequality between temporary workers and continuing employees in permanent jobs increases when offered wages are analyzed and decreases when comparing accepted wages. These are the ratios that change the most. Finally, although inequality changes with the firing cost, it remains high for the range of firing costs considered in this chapter, suggesting that the effect of this policy is limited in this aspect.

### 2.5.3 WELFARE ANALYSIS

Following Flinn [2006] and Flabbi [2010a], this chapter exploits the stationary nature of the model to analyze the long-run welfare impact of changes in the policy parameters (mainly the firing cost) under the two different assumptions about the labor market institution: when temporary contracts are allowed and when they are not. To define a long-run measure of welfare, it is important to recall that at any point in time workers are unemployed, employed under a permanent contract or employed under a temporary contract. Similarly, at any point in time a firm can have a permanent or temporary job vacancies filled or they can be searching to fill their vacancies. The latter is not taken into account because unfilled vacancies have, by definition, a value of zero (free-entry condition). In this context, the following *Social Welfare* function is defined:

$$\begin{aligned}
 S(\tau, \phi, \Psi) = & u(\tau, \phi, \Psi)U_u(\tau, \phi, \Psi) + e_{OP}(\tau, \phi, \Psi) [\bar{W}_{OP}(\tau, \phi, \Psi) + \bar{J}_{OP}(\tau, \phi, \Psi)] \\
 & + e_{IP}(\tau, \phi, \Psi) [\bar{W}_{IP}(\tau, \phi, \Psi) + \bar{J}_{IP}(\tau, \phi, \Psi)] + e_T [\bar{W}_T(\tau, \phi, \Psi) + \bar{J}_T(\tau, \phi, \Psi)]
 \end{aligned} \quad (2.32)$$

where:  $\tau = (\tau_P, \tau_T)$ ,  $\phi = (\phi_P, \phi_T)$ ,  $U_u(\tau, \phi, \Psi)$  is the unemployed agents' welfare,  $\bar{V}_j(\tau, \phi, \Psi)$  is the average workers' welfare ( $j = OP, IP, T$ ) and  $\bar{J}_j(\tau, \phi, \Psi)$  is the average welfare of firms with filled vacancies ( $j = OP, IP, T$ ). Note also that  $e_{OP}(\tau, \phi, \Psi) = e_P(\tau, \phi, \Psi) \Pr(OP)$  and  $e_{IP}(\tau, \phi, \Psi) = e_P(\tau, \phi, \Psi)(1 - \Pr(OP))$ . To implement equation (2.32) it is necessary to define the individual contribution to the

Social Welfare function:

$$\begin{aligned}
U_u(\tau, \phi, \Psi) &= \int_0^{\min\{x_{IP}^*, x_T^*\}} U \left[ \frac{f_P(x)}{F_P(x_{IP}^*)} I_{[x_{IP}^* \leq x_T]} + \frac{f_T(x)}{F_T(x_T^*)} (1 - I_{[x_{IP}^* \leq x_T]}) \right] dx \\
\bar{W}_j(\tau, \phi, \Psi) &= \int_{x_j^*}^{\infty} W_j(x) \left[ \frac{f_P(x)}{1 - F_P(x_j^*)} \right] dx \quad j = IP, OP \\
\bar{W}_T(\tau, \phi, \Psi) &= \int_{x_T^*}^{\infty} W_T(x) \left[ \frac{f_T(x)}{1 - F_T(x_T^*)} \right] dx \\
\bar{J}_j(\tau, \phi, \Psi) &= \int_{x_j^*}^{\infty} J_j(x) \left[ \frac{f_P(x)}{1 - F_P(x_j^*)} \right] dx \quad j = IP, OP \\
\bar{J}_T(\tau, \phi, \Psi) &= \int_{x_T^*}^{\infty} J_T(x) \left[ \frac{f_T(x)}{1 - F_T(x_T^*)} \right] dx
\end{aligned}$$

Equation (2.32) is then used to evaluate changes in welfare (total, workers' and firms' welfares) when the firing cost changes in the case where temporary contracts are allowed and in the case where they are not allowed. Note that equation (2.32) is the analog to the criterion used by Hosios [1990] in his labor market efficiency study when two types of jobs exist.

Figure 2.13 shows the ratio between the level of welfare reached when temporary contracts are not allowed and when they are allowed, for each degree of labor protection. Note that for any firing cost below 1.7 the benchmark firing cost the total welfare is greater in an economy without temporary contracts. The second observation that can be made is that the relative welfare decreases when the firing cost increases. When the firing cost is low, the level of welfare is higher in an economy without temporary contracts. In this case what matters is the possibility of productivity gains in permanent contracts. However, when firing costs are rather high, the level of welfare in an economy with both types of contracts increases (reducing the relative welfare) and the degree of flexibility becomes more valuable. Temporary contracts make agents better off only if the firing cost reaches high levels. Finally, the shape of the relative

welfare means that stringent labor protection generates important trade offs in terms of productivity gains and flexibility.

## 2.6 CONCLUDING REMARKS

This chapter presents a search and matching model with the following features: First, it has a dual labor market represented by two types of contracts, permanent and temporary, and the use of both is endogenously determined as part of the equilibrium. Second, labor protection is incorporated in the form of firing costs to analyze its relationship with the equilibrium share of temporary contracts. Finally, it incorporates the possibility of productivity gains in permanent jobs. This model is structurally estimated using likelihood methods for the Chilean labor market. In the estimation procedure only supply side data is used and the identification strategy, particularly for the technological or demand side parameters, is discussed. Finally, counterfactual and policy experiments are performed to quantitatively evaluate the role of labor protection legislation and the use of temporary contracts in unemployment, welfare, and inequality. Two main assumptions that depart from the literature are made. First, it is assumed that there are two types of jobs in the market, permanent and temporary; hence, there is also a productivity (and wage) distribution associated with each type of job. This assumption allows for the fitting of overlapping wage distributions. Second, temporary jobs have a predefined duration (possibly more than 12 months), are not subject to firing costs, and are not necessarily converted into a permanent job at the end of the contract.

The estimation results indicate that both temporary and permanent contracts survive in equilibrium, and only 25% of the available vacancies are for permanent contracts. This reflects large differences in vacancy costs (US\$45 vs. US\$6). In terms

of the dynamics of the labor market, the magnitude of the parameters suggests that temporary jobs arrive more frequently than permanent jobs (2.6 times faster) and that the workers meeting vacancies with permanent contracts draw, on average, 30% higher productivities than the workers meeting vacancies with temporary contracts. With respect to wages, workers receive wage offers that are, on average, 25% higher when they meet firms with permanent contracts than when they meet firms with temporary ones. Once the job is accepted that difference becomes 60%, on average. Finally, the long run unemployment rate is about 4.9%.

The counterfactual and policy experiments results indicate that when the costs of posting vacancies are different, temporary contracts survive even if there is no firing cost. Then, as the firing cost increases, fewer permanent job vacancies reduce the rate at which they arrive, while more temporary job vacancies accelerate its arrival rate. Temporary jobs magnify the effect of firing costs on permanent job arrival rates. Even though labor protection is useful in reducing unemployment, temporary contracts balance out this effect leaving unemployment practically unchanged. Meanwhile, labor protection increases the (equilibrium) employment rate in jobs with temporary contracts. The effects on employment and unemployment rates discussed above implies that there is a strong substitution effect between both types of jobs. With respect to inequality, the negative effect of firing costs on wages is barely compensated with the existence of temporary contracts. Hence, inequality is persistent. Finally, welfare analysis indicates that temporary contracts generate welfare gains only if labor protection is high.

Some policy implications can be drawn from these results. First, temporary contracts increase flexibility but they do not make agents better off. Second, limiting the use of temporary contracts (in an extreme case, eliminating them) can increase welfare only if labor protection is not stringent. Therefore, stringent labor protec-

tion generates important trade offs between productivity and flexibility. Hence, labor protection levels matter in terms of welfare.

Table 2.1: Number of Employments by Type (CASEN, 2006)

	All		Unskilled		Skilled	
	Obs	Percent	Obs	Percent	Obs	Percent
Permanent	15,608	64.95	12,970	62.07	2,638	84.17
Fixed Tem	3,121	12.99	2,806	13.43	315	10.05
Per Task	4,955	20.62	4,803	22.99	152	4.85
Internship	49	0.2	43	0.21	6	0.19
Other Temporary	296	1.23	273	1.31	23	0.73
Permanent	15,608	64.95	12,970	62.07	2,638	84.17
Temporary	8,421	35.04	7,925	37.94	496	15.82

Note: Temporary includes Fixed-Term, Per Task, Internship and Other Temporary. Sample: Men, head of household, between 25 and 60 years old, and without college degree.

Table 2.2: Number of Employments by Type and Age (CASEN, 2006)

	All			Unskilled			Skilled		
	Obs	%Row	%Col	Obs	%Row	%Col	Obs	%Row	%Col
Permanent									
<= 30	1,564	61.97	10.02	1,249	59.00	9.63	315	77.40	11.94
31 – 40	4,931	63.83	31.59	3,987	60.49	30.74	944	83.25	35.78
41 – 50	5,560	65.26	35.62	4,732	62.66	36.48	828	85.54	31.39
51 – 60	3,553	67.55	22.76	3,002	64.77	23.15	551	88.16	20.89
Total	15,608	64.95	100.00	12,970	62.07	100.00	2,638	84.17	100.00
Temporary									
<= 30	960	38.03	11.40	868	41.00	10.95	92	22.60	18.55
31 – 40	2,794	36.17	33.18	2,604	39.51	32.86	190	16.75	38.31
41 – 50	2,960	34.74	35.15	2,820	37.34	35.58	140	14.46	28.23
51 – 60	1,707	32.45	20.27	1,633	35.23	20.61	74	11.84	14.92
Total	8,421	35.05	100.00	7,925	37.93	100.00	496	15.83	100.00

Note: Temporary includes Fixed-Term, Per Task, Internship and Other Temporary. Sample: Men, head of household, between 25 and 60 years old, and without college degree.

Table 2.3: Average Duration by Type of Employment (CASEN, 2006)

	All		Unskilled		Skilled	
	Average	S.D.	Average	S.D.	Average	S.D.
Permanent	113.21	107.51	110.87	106.52	124.71	111.57
Fixed Tem	44.62	78.95	43.97	79.03	50.42	78.03
Per Task	37.14	80.32	37.06	80.73	39.74	66.50
Internship	25.89	56.15	26.13	58.12	24.17	43.49
Other Temporary	37.45	80.61	38.75	83.32	22.05	32.19
Permanent	113.21	107.51	110.87	106.52	124.71	111.57
Temporary	39.86	79.78	39.50	80.18	45.51	73.03

Note: Temporary includes Fixed-Term, Per Task, Internship and Other Temporary. Sample: Men, head of household, between 25 and 60 years old, and without college degree.

Table 2.4: Average Hourly Wage by Type of Employment

	All		Unskilled		Skilled	
	Average	S.D.	Average	S.D.	Average	S.D.
Permanent	2.27	2.15	1.73	1.22	4.92	3.41
Fixed Tem	1.61	1.30	1.38	0.85	3.64	2.41
Per Task	1.30	0.98	1.24	0.84	3.17	2.33
Internship	1.49	1.27	1.52	1.33	1.34	0.70
Other Temporary	1.38	1.37	1.18	0.93	3.66	2.93
Permanent	2.27	2.15	1.73	1.22	4.92	3.41
Temporary	1.42	1.13	1.29	0.85	3.47	2.41

Note: Temporary includes Fixed-Term, Per Task, Internship and Other Temporary. Sample: Men, head of household, between 25 and 60 years old, and without college degree.



Table 2.5: Proportion of Employments by Economic Activity and Type (CASEN, 2006)

	Skilled		Unskilled	
	Permanent	Temporary	Permanent	Temporary
Agriculture, Hunting, Forestry and Fish	82.5	17.5	52.5	47.5
Mining and Quarrying	83.7	16.3	70.6	29.4
Manufacturing Electricity, Gas and Water	87.3	12.7	79.1	21.0
Construction	89.8	10.2	77.4	22.6
Wholesale, Retail and Restaurants	60.1	39.9	29.3	70.7
Transport, Storage and Communication	92.3	7.7	83.6	16.5
Financing, Insurance and Real State	83.6	16.4	76.2	23.8
Community, Social and Personal Services	89.6	10.4	80.8	19.2
Total	84.0	16.0	79.8	20.2
	84.2	15.8	62.0	38.0

Note: Temporary includes Fixed-Term, Per Task, Internship and Other Temporary. Sample: Men, head of household, between 25 and 60 years old, and without college degree.

Table 2.6: Sample Descriptive Statistics

	Mean	S.D.
Wages (Dollars per Hour)		
$w e$	2.46	2.04
$w e_P$	2.69	2.21
$w e_T$	1.65	0.85
<i>Ratio</i>	1.63	
Duration (Months)		
$t u$	16.57	12.28
% Left Censored	6.14	
% Right Censored	15.79	
$t e_P$	105.93	81.78
% Left Censored	2.12	
% Right Censored	81.52	
$t e_T$	26.01	23.89
% Left Censored	1.54	
% Right Censored	61.4	
Transitions (Percent)		
$u \rightarrow e_P$	22.8	
$u \rightarrow e_T$	61.4	
Share by Type of Contract (Percent)		
Permanent	77.92	
Temporary	22.08	

Sample: Men, head of household, between 25 and 60 years old, and without college degree.

Table 2.7: Estimated Parameters

	Param.	Std.Err.(*)
$\alpha_w^P$	0.1362	0.0004
$\alpha_w^T$	0.3475	0.0022
$\lambda_P$	0.0015	0.000001
$\lambda_T$	0.0127	0.00004
$x_T^*$	1.1256	0.0459
$x_{IP}^*$	1.1211	0.0598
$x_{OP}^*$	1.3422	0.0598
$rU$	1.0928	0.0445
$\sigma_\epsilon$	0.2430	0.0072
$\mu_P^x$	-1.4306	0.0003
$\sigma_P^x$	1.6179	0.0016
$\mu_T^x$	-0.9859	0.0099
$\sigma_T^x$	1.0932	0.0066
No. Obs.		2,170
Loglik		-4,829
F-test $\alpha_w^P = \alpha_w^T$		12,967
F-test $\mu_P^x = \mu_T^x$		231
$\sigma_P^x = \sigma_T^x$		

(\*) Asymptotic standard errors.

Table 2.8: Technological and Preference Parameters

	Param.	Std.Err.
Cobb Douglas Matching Function(*)		
$\eta$	0.2493	0.0008
$q$	0.3841	0.0025
$k_P$	45.3040	1.0640
$k_T$	6.2272	0.4860
$b$	-4.0413	0.2838
Exponential Matching Function		
$\eta$	0.2675	0.0010
$q$	0.5093	0.0033
$k_P$	31.8448	0.7622
$k_T$	4.8135	0.3736
$b$	-4.0413	0.2838

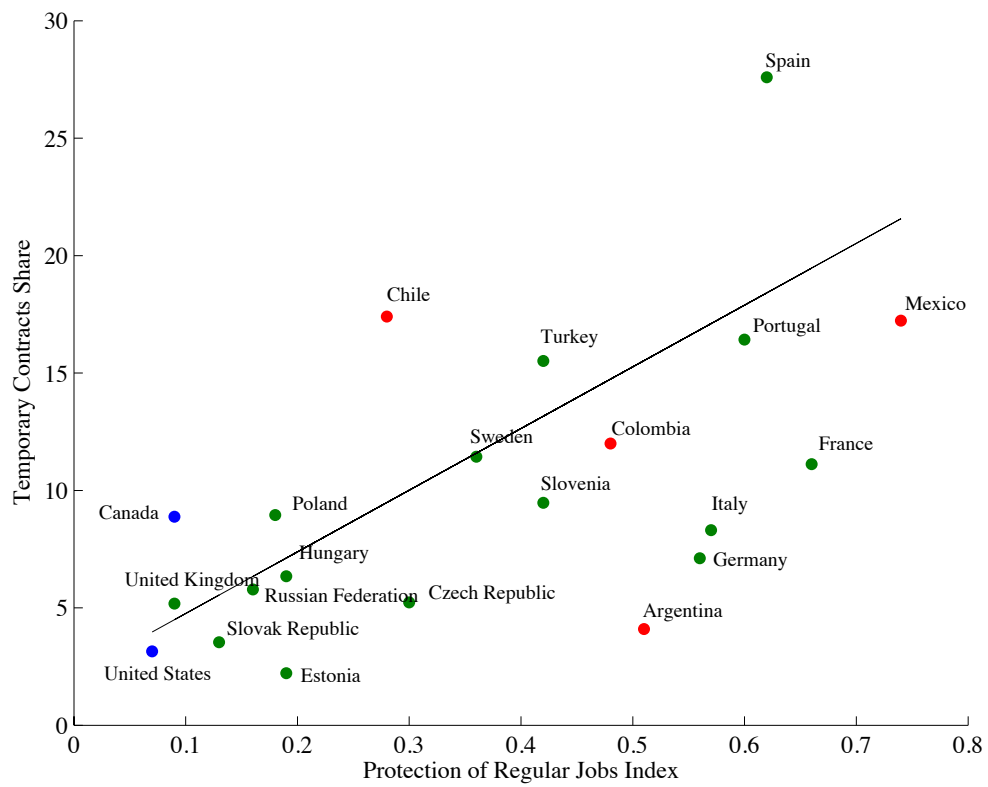
(\*) Belani et.al. (2002):  $\gamma = 0.85$ . Note: Standard Errors calculated using delta method.

Table 2.9: Predicted Values

	Value	Std.Err. (*)	Data
Productivity			
$E(x_P)$	0.885	0.00206	n.a.
$V(x_P)$	9.957	0.10310	n.a.
$E(x_T)$	0.678	0.01159	n.a.
$V(x_T)$	1.060	0.05803	n.a.
Offered Wages			
$E(w_{OP})$	1.106	0.02703	n.a.
$E(w_{IP})$	1.217	0.02702	n.a.
$E(w_T)$	0.886	0.01648	n.a.
Accepted Wages			
$E(w_{OP} e_P)$	2.857	0.08946	2.69
$E(w_{IP} e_P)$	2.719	0.09172	2.69
$E(w_T e_T)$	1.704	0.04459	1.65
Labor Market Status			
$u$	0.049	0.00291	0.05
$e_P$	0.743	0.00206	0.74
$e_T$	0.209	0.00497	0.21
Labor Market Dynamics			
$h_u$	0.074	0.00563	0.060
$h_{e_P}$	0.001	0.00001	0.009
$h_{e_T}$	0.013	0.00004	0.038

(\*) Standard Errors calculated using delta method.

Figure 2.1: Share of Temporary Jobs and Strictness of Protection for Regular Jobs



Sources: Pierre and Scarpetta [2004], Tokman and Martinez (1999), OECD Stats.

Figure 2.2: Sample Wages Densities by Type of Contract

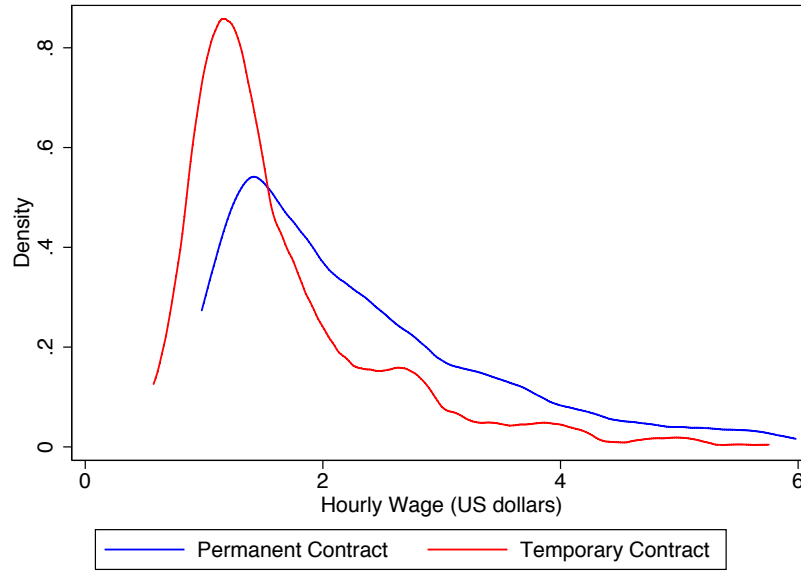


Figure 2.3: Sample Wages Densities for Permanent Contracts by Tenure



Figure 2.4: Labor Market Tightness and Proportion of Vacancies of Permanent Jobs

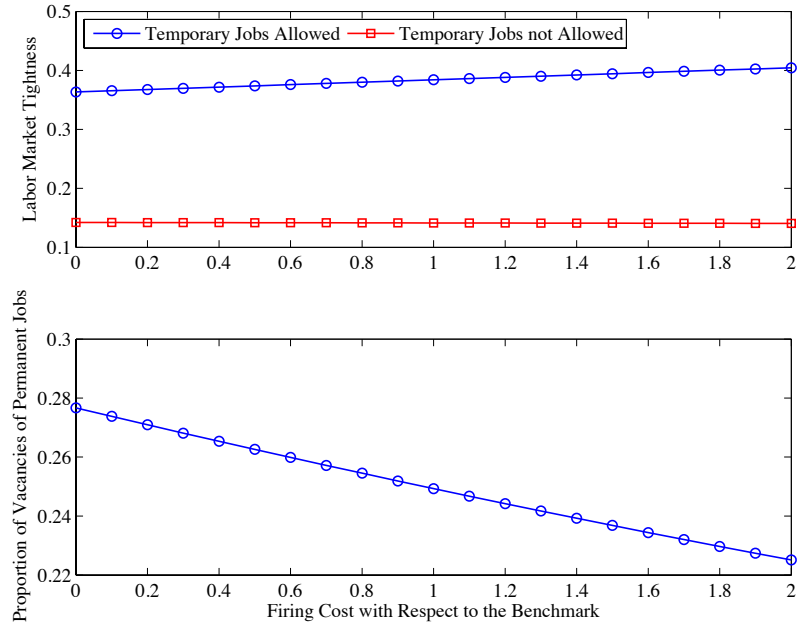


Figure 2.5: Permanent and Temporary Job Arrival Rates

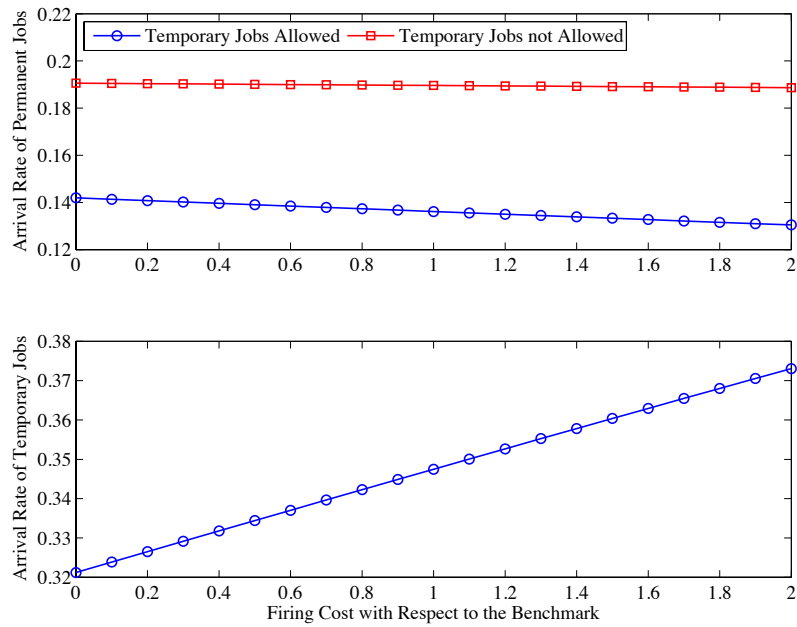




Figure 2.6: Unemployment Rate and Hazard Rate from Unemployment

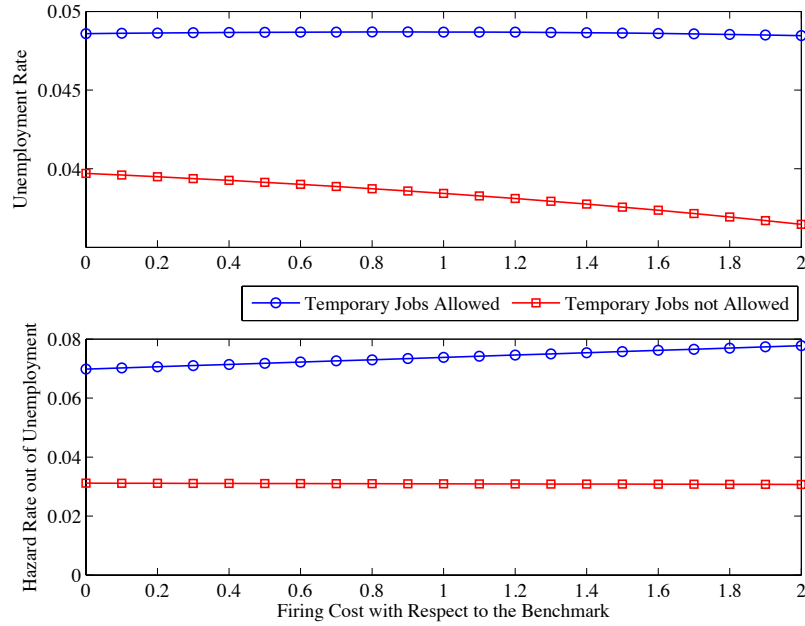


Figure 2.7: Employment Rate and Hazard Rate of Permanent Jobs

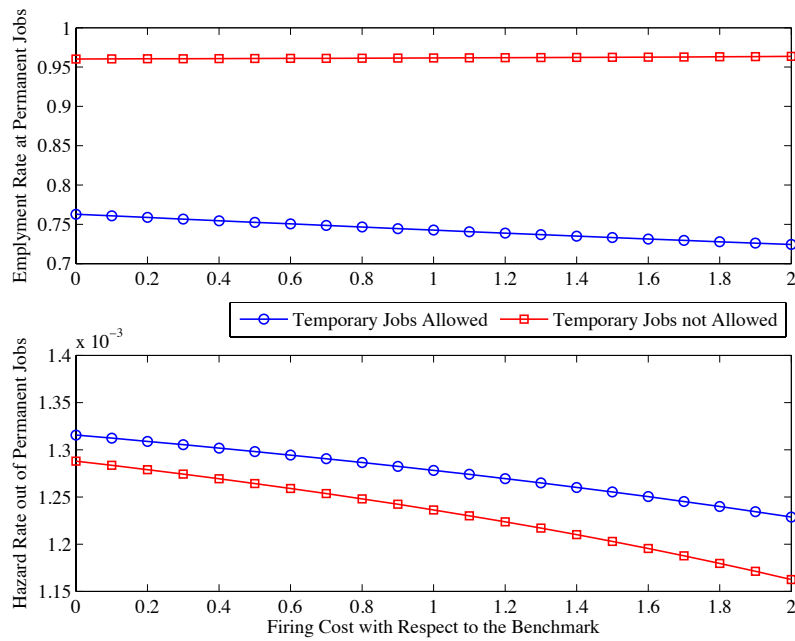


Figure 2.8: Employment Rate and Hazard Rate of Temporary Jobs

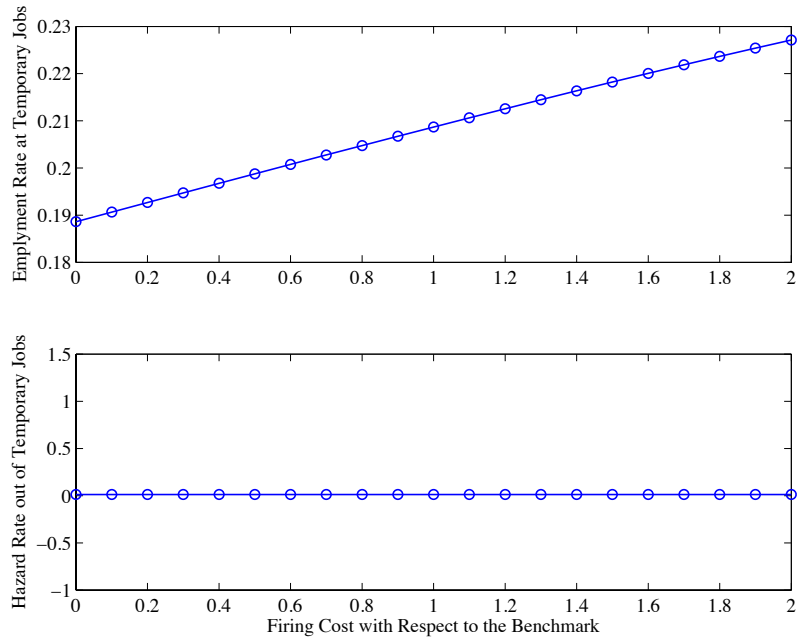


Figure 2.9: Reservation Productivities

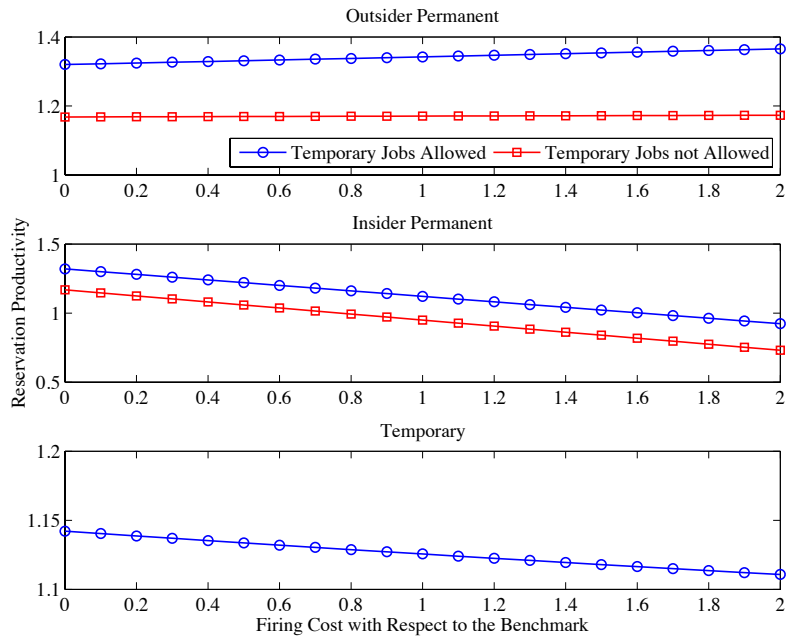


Figure 2.10: Average Offered Wages

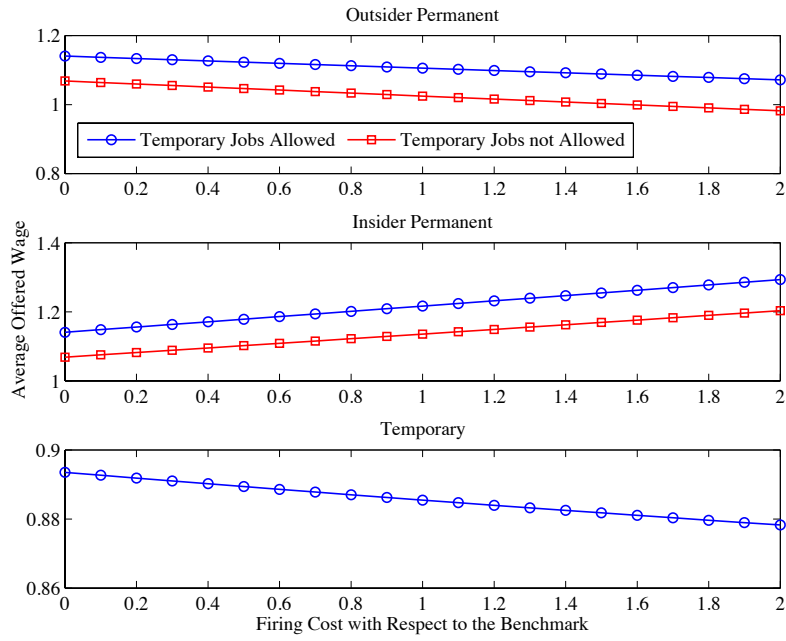


Figure 2.11: Average Accepted Wages

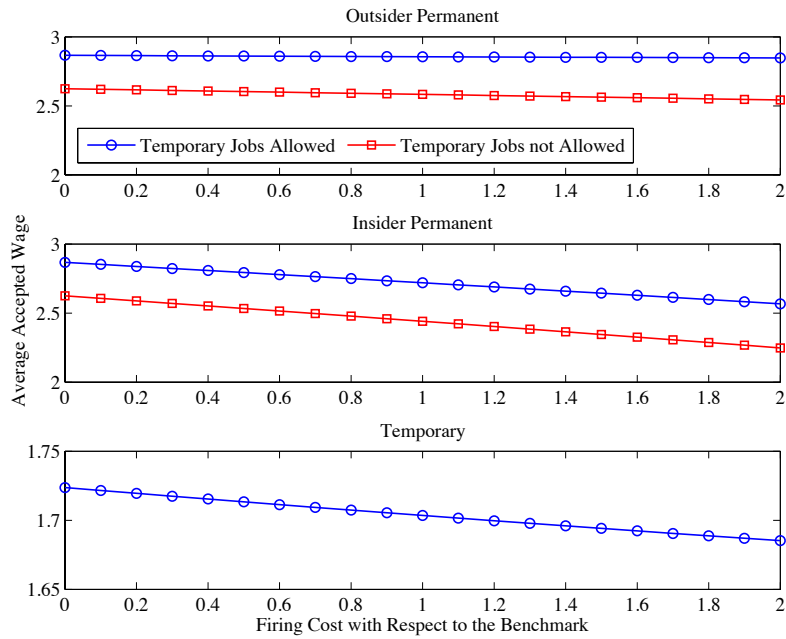


Figure 2.12: Wage Ratios (Inequality)

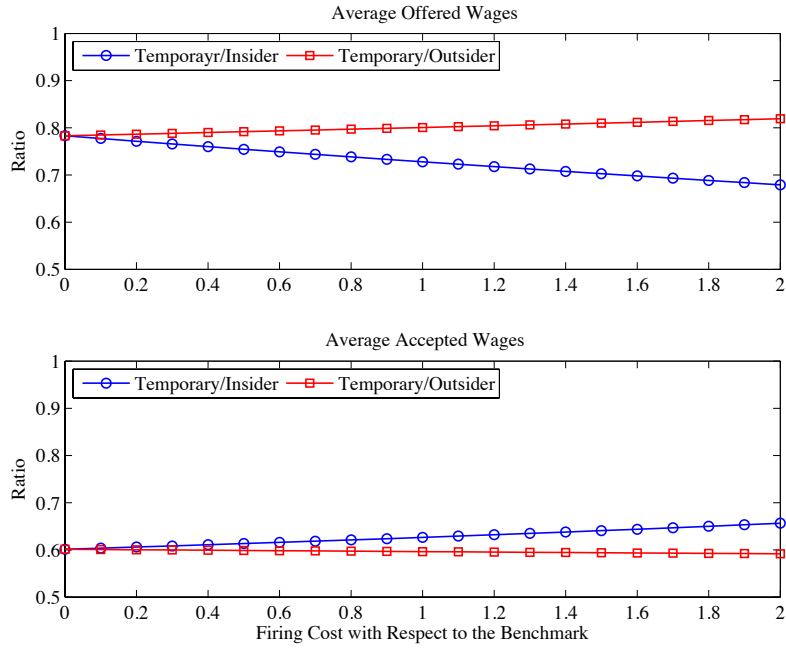
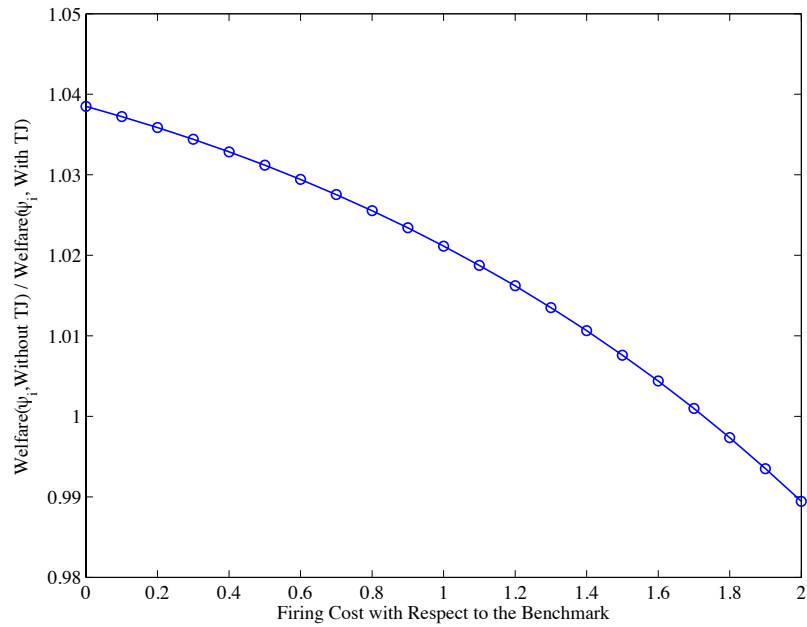


Figure 2.13: Welfare Analysis



## CHAPTER 3

# LIFETIME INEQUALITY MEASURES FOR AN EMERGING ECONOMY: THE CASE OF CHILE

### 3.1 INTRODUCTION

Cross-section and lifetime measures of inequality are different, because the latter reflects long run resources available to individuals while the former does not. Moreover, cross-section distributions of earnings are just snapshots of the workforce [Gottschalk and Moffitt, 1994]. Therefore, the use of current income to perform inequality studies can be misleading due to the existence of a transitory component in the current income [Blundell and Preston, 1998, Krueger and Perri, 2006]. This emphasizes the dynamic dimension of inequality. Along these lines, Flabbi and Leonardi [2010] indicate that earnings inequality is not simply described by the current earnings but also by mobility across jobs and labor market states. Therefore, lifetime inequality measures should take into account labor market states and lifetime wage profiles. Buchinsky and Hunt [1999] and Bowlus and Robin [2004] complement this idea suggesting that individual welfare not only depends on the current employment position but also on the expected evolution of this position over time.

Many studies have analyzed and compared economies using this lifetime perspective, however, they all focus on the United States, Canada or Europe. In the case of emerging economies, the literature is scarce, perhaps because of data limitations.

These economies also have the particularity that in general they have relatively more regulated labor markets and high cross-sectional measures of inequality as can be seen in figure 3.1. This chapter seeks to fill this gap and its focus is on the analysis of wage inequality using the lifetime perspective for an emerging economy. In doing so, some additional evidence on the link between labor market regulation and low wage flexibility and mobility is provided. This chapter focuses on the Chilean labor market for two reasons: first, Chile is one of the countries with the highest cross-sectional (and most persistent) income inequality, not only in Latin America but also worldwide; and second, Chile has a rich dataset with labor market histories. There are many inequality studies for the case of Chile but almost all of them use a cross-section distribution of earnings in analyzing inequality. Therefore, this chapter contributes to improving the standard empirical measures of inequality for Chile providing lifetime measures of inequality.

This chapter uses a search-theoretic framework to analyze long-run inequality through the lens of the labor market. In analyzing income inequality, the job market outcomes play a key role (see figure 3.2)<sup>1</sup>. In particular, using the Social Protection Survey dataset for Chile, a structural search model with on-the-job search is estimated and simulations of careers are used to construct lifetime measures of inequality. The lifetime welfare is then measured as the sum of the discounted values of the simulated labor incomes [Flinn, 2002a, Flabbi and Leonardi, 2010]. The estimation controls for (observed) heterogeneity in education assuming segmented markets for skilled and unskilled workers. As is usual in the estimation of this type of models, two issues emerge: the first is the right censoring problem and the second is the so called Initial Conditions Problem [Flinn, 2002a]. Both problems are controlled in the estimation.

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<sup>1</sup>This figure also indicates that Chile has the highest level of inequality in the OECD countries (Chile became an OECD member on 7 May 2010)

Finally, the model is used to perform three experiments to isolate the mobility and distribution effects on inequality and to find differences in the labor market dynamics by age. These experiments are done comparing the Chilean labor market with a benchmark economy that has a more flexible labor market (the United States); calculating the marginal effects of the model parameters on lifetime inequality; and estimating mobility differentials by age.

Results indicate that inequality is not only high in a cross-sectional perspective, but also in a lifetime perspective and that the regulation of the labor market, reflected in the estimated parameters of the model, matters and has an impact on the degree of mobility in the labor market. This, in turn, has an impact on lifetime measures of inequality: a more flexible labor market generates a less unequal lifetime earnings distribution. This holds regardless of the skill level. Finally, the labor market is more mobile and comparatively less unequal for younger worker.

## 3.2 RELATED LITERATURE

This chapter is closely related to the literature on structural estimation of partial equilibrium search models. The two closest articles are Flinn and Heckman [1982] and Flinn [2002a]. The former was the first to present a method to estimate this type of model and the latter extends that procedure to estimate models with on-the-job search.

The second group of related literature analyzes long-run welfare inequality and has two streams. The first is the study of income or earnings dynamics directly, in which some ARMA-type processes (or more complicated processes) are fitted to longitudinal earnings data to decompose earnings in its transitory and permanent components. Some examples are Gottschalk and Moffitt [1994] and Moffitt and Gottschalk [2002]

for the United States, Gangl [2005] who compares Europe and the United States, Chen [2009] who uses data for Canada, the United States, United Kingdom and Germany, Bonhomme and Robin [2009] who use data on France, and Lilla and Staffolani [2009] for the Italian labor market. As was mentioned in the previous section, this literature is highly concentrated on the United States, United Kingdom, Canada and European Countries. For the case of Chile there is one paper, Huneeus and Repetto [2005], who analyze the dynamics of earnings in the life cycle [in line with for example Low et al., 2010] and it is the closest in spirit to this chapter. They find that earnings are highly persistent, and therefore, there is little mobility of individuals across the distribution.

The second stream, which is the closest in terms of the approach used in this chapter, is based on the search-theoretic framework and analyzes long-run inequality through the lens of the labor market (estimating a structural search model). This literature started with Flinn [2002a] comparing the United States and Italy and continued with Bowlus and Robin [2004], who estimate a non-stationary search model for the United States, Flabbi and Mabili [2010], who estimate a model of household search for the United States, and finally, Flabbi and Leonardi [2010], who compare earnings distribution across time in the United States. It is important to mention that Postel-Vinay and Turon [2010] provide a link between these two streams of the literature analyzing the relationship between the dynamics of the labor market with search frictions and the dynamics of the earning process.

Finally, the third group of related literature analyzes inequality in Chile. The literature in this area is vast but practically all of the papers have used cross-section distribution of earnings in analyzing inequality. Some examples are: Beyer [1995], Beyer [1997], Contreras [1996], Cowan and De Gregorio [1996], Contreras [2002], Bravo and Marinovic [1997] and Larrañaga [2009]. The main conclusions of this literature are: First, Chile is one of the countries with the highest cross-section income inequality



worldwide; second, cross-section income inequality has been high and persistent across time (particularly in the nineties); and finally, the main factor in explaining between group cross-section income inequality is education. Recently, Sapelli [2011] has found that even though earnings inequality has been high and persistent overall, positive changes have been observed for young individuals.

### 3.3 THE MODEL

This section briefly describes the model setup and its solution. The model used in this chapter to simulate the dynamics of the Chilean labor market is a standard partial equilibrium random search model with on-the-job search in the line of Flinn [2002a]. It is assumed that the environment is stationary and that the economy is populated by a continuum of infinitely lived risk neutral<sup>2</sup> homogeneous agents. At each point in time agents can be unemployed and searching for a job<sup>3</sup> or employed but looking for new job opportunities. While unemployed, agents receive an instantaneous utility, or possibly disutility,  $b$  (interpreted as the value of leisure) and job offers which arrive according to a Poisson process with parameter  $\lambda_U$ . Job offers take the form of a wage ( $w$ ) drawn from an exogenous distribution  $G(w)$ <sup>4</sup>.

While employed, on the other hand, agents receive an instantaneous utility (and wage)  $w$ . Each job can be terminated because an acceptable new offer arrives, or because the worker receives a reallocation shock (for which the resulting new state can be either unemployed or employed in a new job), or due to the arrival of an involuntary separation shock which leads directly to the unemployment state. Job

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<sup>2</sup>This means that the instantaneous utility flow enjoyed from a flow of income  $y$  is  $U(y) = y$ .

<sup>3</sup>Participation decisions are not modeled in this chapter.

<sup>4</sup>The behavior of firms is not explicitly modeled and it is assumed that it is summarized in the wage distribution.

offers while employed arrive according to a Poisson process with parameter  $\lambda_E$  and, as before, they are represented by a wage rate ( $w$ ) drawn from the distribution  $G(w)$ . Reallocation shocks, on the other hand, arrive according to a Poisson process with parameter  $\lambda_R$ . When this type of shock arrives the worker's job is terminated and he/she immediately receives a new offer (which can be acceptable or not) without going to the unemployment state. Following Flabbi and Leonardi [2010], this type of shock is incorporated in the model as an alternative to empirically account for job-to-job transition with wage cuts and can be theoretically interpreted as an approximation of institutions such as the advance notice received by the worker when a layoff occurs<sup>5</sup>. Finally, involuntary separations arrive according to a Poisson process with parameter  $\eta$ . Workers discount the future at an exogenous and constant rate  $\rho > 0$  and seek to maximize the expected discounted sum of future utility flows.

Denote the value of unemployment by  $U$  and the value of employment for a worker whose wage is  $w$  by  $W(w)$ . As is discussed in detail in Flinn [2002a] and Flabbi and Leonardi [2010], the optimal decision rules in this model have a reservation value property and they depend on the type of transition. If the agent receives an offer while unemployed, he/she will accept the offer if the wage is greater than the reservation wage ( $w^*$ ), which satisfies  $W(w^*) = U$ . The same holds when a worker receives a reallocation shock because his/her alternative state is unemployment. On the other hand, if the agent receives an offer while on the job, the outside option corresponds to the current wage which means that the agent will accept the offer only if the new wage (say  $w'$ ) is greater than the current wage ( $w$ ). To summarize the optimal decision

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<sup>5</sup>To account for job-to-job transitions with wage cuts, which conditional on Flinn [2002a] model are probability zero events, the literature has typically used measurement error in wages in the estimation [Eckstein and van den Berg, 2007]. However, there can be in practice job-to-job transition with wage cuts if other job amenities are considered; but because those amenities are not modeled here, this type of event is inconsistent with the model. Here is where the idea of Flabbi and Leonardi [2010] can be used.

rules write:

$$\begin{aligned}
 d_{U,R}(w) &= \begin{cases} \text{Accept offer } w & \iff w \geq w^* \\ \text{Unemployment state} & \iff w < w^* \end{cases} \\
 d_E(w) &= \begin{cases} \text{Accept new offer } w' & \iff w' \geq w \\ \text{Continue in current job} & \iff w' < w \end{cases}
 \end{aligned} \tag{3.1}$$

Using the values of unemployment and employment, the decision rules and the parameters, it is possible to write the flow value of unemployment as:

$$\rho U = b + \lambda_U \int_{w^*}^{\infty} [W(w) - U] dG(w) \tag{3.2}$$

Equation (3.2) indicates that unemployed agents receive a flow utility  $b$  and that at rate  $\lambda_U$  they get a job offer, which if taken ( $w \geq w^*$ ) generates a capital gain of  $W(w) - U$ . In turn, the flow value of taking a job with current wage  $w$  can then be written as:

$$\begin{aligned}
 \rho W(w) &= w + \lambda_E \int_w^{\infty} [W(w') - W(w)] dG(w') + \lambda_R \int_{w^*}^{\infty} [W(w') - W(w)] dG(w') \\
 &\quad + (\eta + G(w^*)\lambda_R)[U - W(w)]
 \end{aligned} \tag{3.3}$$

According to equation (3.3), an employed agent receives a wage rate  $w$  and new offers, reallocation and terminations shocks arrive at rates  $\lambda_E$ ,  $\lambda_R$  and  $\eta$ , respectively. In the case of a new offer, if it is good enough, meaning that  $w' \geq w$ , the worker changes his/her job and a capital gain of  $W(w') - W(w)$  is realized. When a reallocation shock arrives, on the other hand, there are two possibilities: if the new offer after the job termination is taken, a realized capital gain (or possibly loss) of  $W(w') - W(w)$  occurs, while if it is not taken, the worker becomes unemployed with a capital loss of  $U - W(w)$ . Finally, when an involuntary separation occurs the capital loss will also be  $U - W(w)$ .

Combining equations (3.2) and (3.3) with the equilibrium conditions  $W(w^*) = U$  and  $W(w) = W(w')$  that generate the decision rules in (3.1) it is possible to write<sup>6</sup>:

$$w^* = \gamma(w^*)b + [\gamma(w^*)\lambda_U - \lambda_E - \lambda_R] \int_{w^*}^{\infty} W(w')dG(w') \quad (3.4)$$

$$W(w) = \theta(w) \left\{ \begin{array}{l} w + [\eta + \lambda_R G(w^*)] W(w^*) \\ + \lambda_E \int_w^{\infty} W(w')dG(w') + \lambda_R \int_{w^*}^{\infty} W(w')dG(w') \end{array} \right\} \quad (3.5)$$

where  $\gamma(w^*) = \frac{(\rho + (\lambda_E + \lambda_R)\tilde{G}(w^*))}{(\rho + \lambda_U\tilde{G}(w^*))}$  and  $\theta(w) = \frac{1}{(\rho + \eta + \lambda_R + \lambda_E\tilde{G}(w))}$ .

The first equation solves for the reservation wage  $w^*$ , while the second solves for the function  $W(w)$ . Once both are known, the solution of the model is fully characterized, and for a given set of parameters and assumptions about the parametric form of the wage distribution, can be used to simulate labor market careers. It is important to mention that it is possible to show that Blackwell's sufficient conditions hold and, therefore, there is a unique fixed point for  $w^*$  and  $W(w)$ .

### 3.4 ESTIMATION PROCEDURE

The model is estimated using Maximum Likelihood Methods with supply side data for the Chilean labor market. This section describes the data available for estimation and briefly discusses the likelihood function, the identification strategy and the potential econometric issues faced in estimation.

#### 3.4.1 DATA

Estimating job search models with on-the-job search requires a rich environment of information because not only are unemployment to employment transitions needed

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<sup>6</sup>Appendix B.1 presents the detailed derivation of the equations of the model and the computational algorithm used to solve equations (3.4) and (3.5).

but also job to job transitions. In other words, information about labor market histories or working cycles is needed [Eckstein and van den Berg, 2007]. This feature of the data is hard to find for developing economies which, in part, explains why the literature has concentrated only on the United States, Canada and Europe. This chapter uses the Chilean *Social Protection Survey* (Encuesta de Protección Social or EPS), from the Subsecretaría de Previsión Social of the Chilean government<sup>7</sup>, which was designed precisely to build a panel of labor market histories.

The survey was conducted in 2002, 2004, 2006 and 2009 and in each survey, the interviewer explicitly asked about the events (dates of different states in the job market and average wages in each job) in the years after the last survey in which the individual participated. For the estimations only the surveys conducted in 2004 and 2006 are used, and to avoid left and double censoring in the data, the data of the last spell in the 2002 survey is used to correct the first spells observed in the 2004 survey. The reasons for focusing only on these two surveys are twofold: individuals were asked only about their labor histories but not about the wage in each event in the 2002 survey, and the 2009 survey conveys information contaminated with the effects of the 2008 financial crises on the labor market. In any case, working only with these two surveys generates a time span from January 2002 to September 2007, which means that almost 6 years of labor market transitions are available for the estimation.

Two problem arose in the appending of the 2004 and 2006 surveys. First, there were overlapping events: events at the end of the 2004 survey overlapped with those at the beginning of the 2006 survey. Two overlapped events were merged if they

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<sup>7</sup>The survey is conducted by the Microdata Center of the Economics Department at the University of Chile with the participation of academics of the University of Pennsylvania and the University of Michigan.

belonged to the same state<sup>8</sup>. Second, there were contained events: events at the end of the 2004 survey were contained in those at the beginning of the 2006 survey. In this case, the events occurring in the 2004 survey were kept since it is assumed that the data on the events that occurred in the same year as the survey is more accurate. As was mentioned before, the last event of the 2002 survey was used only to correct left censoring and, in performing this correction, the criteria described above, when overlapping or contained events problems were found, was also used. The only difference is that information on wages was preserved for the employed spells observed at the beginning of the 2004 survey. Finally, individuals who presented inconsistencies in their histories, had incomplete histories or events with missing information on wages, hours worked or event dates were discarded<sup>9</sup>.

The model assumes that individuals are homogeneous making some sample restrictions necessary in order to guarantee a certain degree of homogeneity consistent with the model. In particular, the estimation sample satisfies the following criteria: males who are actively participating in the labor market and are between 20 and 65 years old. These sample decisions were taken because first, the model presented in the previous section does not explicitly model participation decisions, and second, in the case of women there is a strong selection problem due to participation decisions<sup>10</sup>. Additionally, and because of the important role of education in explaining wage inequality in Chile [Contreras, 2002], the sample was divided into two subsamples by education level: skilled and unskilled workers. The former group consists of individuals who

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<sup>8</sup>For the case of employed workers and to increase the likelihood of merging two events that belong to the same job, information about the type of contract (permanent, fixed term, per service, etc) was also used.

<sup>9</sup>This group of individuals with inconsistencies and missing data represented around 18% of the sample.

<sup>10</sup>According the National Institute of Statistics of Chile the average participation rates in the 2000s were 74 and 38% for men and women, respectively

have completed tertiary education (that is, more than 14 years of schooling), while the latter group did not complete that level of education. Initially, there were 2,892 individuals in the sample with these characteristics (once the inconsistencies were discarded), 688 skilled workers and 2,207 unskilled workers.

The sample size was further reduced due to other problems with the data. First, there were double censored spells in the unemployment state, which could not be used because they generate an identification problem as discussed in the next section (fortunately this reduction only represents 1.9% of the valid sample). Second, to avoid an outliers problem, due to the existence of unrealistically high wages, 5 of the upper and lower percentiles in wages were dropped from the sample (resulting in a reduction of 15% of the valid sample observations). This elimination generated an average wage that is comparable with the literature<sup>11</sup>.

The final sample was then organized in working cycles. Each cycle starts in the unemployment state which is followed by all observed job to job transitions (note that it is possible to observe more than one cycle per individual). Working cycles starts in this state because it resets the dynamics of the model [Flabbi and Leonardi, 2010]. If for some individual, the first event, observed in January 2002, corresponds to an employment state, all transitions were also stored for estimation purposes. However, information differentiating both types of cycles, either starting in unemployment or starting in employment, was stored and exploited in the estimation. Figure 3.3 shows how the cycle is constructed for a hypothetical example of labor market history. After all data manipulations, the estimation has a total of 693 and 2,572 cycles for skilled and unskilled workers, respectively.

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<sup>11</sup>Fuentes et al. [2005], using the National Socio-economic Survey (CASEN), estimate that in 2003 the average monthly real labor income for males was 267,378 pesos (in 2004 pesos). Assuming an average of 48 working hours per week, an hourly wage of 1392.59 Chilean pesos (or 2.28 US dollars) can be estimated.

It is useful to summarize the information available for estimation and to define the notation used in the likelihood function in the following way:

$$\{t_k(i), w_k(i), c_k(i), r_k(i), \chi(i)\}_{i=1}^{N^C}$$

where:  $N^C$  represents the number of cycles observed in the sample,  $t_k(i)$ , for  $k = u, 1, 2, 3$ , corresponds to duration information, measured in months, for the  $k^{th}$  state in the cycle. Note that  $t_1(i)$  represents the duration of both the first job after the unemployment state and the duration of the first observed job when the cycle starts in an employment state. On the other hand,  $w_k(i)$ , for  $k = u, 1, 2, 3$ , is the wage measured in 2004 U.S. dollars per hour for the  $k^{th}$  state in the cycle. Note that  $w_u(i)$  corresponds to the first accepted wage out of the unemployment state while  $w_1(i)$  corresponds to the wage observed in a cycle that starts in an employment state. Left censored spells are represented by  $c_k(i)$ , for  $k = u, 1, 2, 3$ , which are dummy variables that take the value 1 if the spell is censored and zero otherwise. Terminations in unemployment are indicated by  $r_k(i)$ , for  $k = 1, 2, 3$ , which are dummy variables that take the value 1 if a transition between employment and unemployment is observed and zero otherwise. This also means that the cycle is complete. Finally,  $\chi$  indicates if the cycle starts in a unemployment state. It is a dummy variable that takes the value 1 if the unemployment state is observed at the beginning of each cycle and zero otherwise.

Tables 3.1 and 3.2 present descriptive statistics on duration and hourly wages in each state of the cycle, differentiating by the nature of the first event of the cycle (unemployment state or employment state) and by level of education. With respect to the duration information, Table 3.1 indicates that while skilled workers remain unemployed on average two more months than unskilled workers, they keep their jobs for longer periods compared to the unskilled workers. This is true when the



cycle starts in an unemployment spell. On the other hand, when the cycle starts in an employment spell, such differences in the average job duration are not that evident, at least in the case of the first observed job. When the cycle starts in an unemployment spell, the right censoring problem is important because more than 20% of the spells in the unemployment state and in the first job are censored. When the cycle starts in employment, however, this problem becomes even more important. Hence the estimation has to control for this problem in order to avoid censoring bias. The left censored problem does not represent an issue because less than 2% of the spells have unknown starting date.

Wages information, in Table 3.2, shows that in the first job, after being in an unemployment state, skilled workers earn, on average, twice that earned by an unskilled worker. This gap gets even larger in the following job in the cycle. In the transition from the first job, after unemployment, to the second job more than 40% of the wages fall. This figure increases to more than 80% in the transition to the third job. However, this drops in wages should not be large in magnitude because, on average, wages grow in each of these transitions. When the cycles start in an unemployment state the gaps between wages of skilled and unskilled workers are similar to those observed when the cycle starts in an unemployment state. In terms of wage cuts, however, the story is different. Even though in the transition of the first to the second job only 10% of the wages fall, the average wage experiences a reduction. This means that the magnitudes of the wage reductions are large. In the transition to the third job, almost 75% of the wages fall and as a result the average wage also falls. Finally, it is evident that the distribution of wages is more disperse for skilled workers.

### 3.4.2 THE LIKELIHOOD FUNCTION

The estimation procedure used in this chapter, as well as its description, follows Flabbi and Leonardi [2010] closely. However, before presenting the likelihood function, it is important to discuss the fundamental problem faced in estimating search models with on-the-job search with working cycles that start in an employment state: the initial condition problem<sup>12</sup>. Note from the model in section 3.3 that an individual who starts in an unemployment state draws an acceptable wage from a distribution truncated at  $w^*$ , that is:  $\frac{G(w)}{1-G(w^*)}$ . When on the job, on the other hand, the worker draws an acceptable wage from a distribution truncated at its current wage  $w_k$  with  $k = u, 2, 3, \dots$ , that is  $\frac{G(w)}{1-G(w_k)}$ . Because, by construction,  $w_3 \geq w_2 \geq w_u$  the distribution of the  $k^{th}$  job stochastically dominates (at least weakly) the distribution of the  $k^{th} - 1$  job. Therefore, order matters. Now let's consider a worker observed for the first time in an employment state. Without any information on the previous states in the labor market it is impossible to know the order of the job, and hence the distribution that generates the wage. This has implications for the contribution of wages to the likelihood function because those contributions are related precisely with that unknown distribution.

The literature has proposed procedures to address this problem. One option, described in Flinn [2002a], is to find the steady state distribution of wages and assume that the system has reached that state. Another alternative, proposed by Ridder and van den Berg [2003] and used to estimate the arrival rates, uses only data on duration and the wage distribution of the workers initially observed after unemployment. Barlevy and Nagaraja [2010] goes further and propose a method, suitable under some particular assumptions, to estimate these rates using only duration data

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<sup>12</sup>In this chapter the discussion is rather brief and informal. For a formal exposition of the problem see Flinn [2002a].

and completely ignoring wage information (in particular, it exploits heterogeneity in the hazard rates). A third option, used by Flinn [2002a] and Flabbi and Leonardi [2010], is to write the likelihood conditioning on the wage of the first job observed at the beginning of the sample (that is, the first job of the cycles that starts in employment). This last procedure generates consistent estimates at the cost of losing some information.

Whit respect to the first option, since more than a third of the sample, used in the estimations, correspond tot young workers (i.e., those less than 35 years old), it is inappropriate to make the assumption that system has reached the steady state for this group of workers. On the other hand, since the analysis of lifetime inequality requires both, the transitions across the state and the wage distribution, the second group of approaches provide only partial information. Hence, given this reasons, the third approach is the most suitable for the particular application of this chapter.

To construct the likelihood function it is necessary to define the contributions of the data in each state to that function. In order to describe the contribution of the duration data, the hazard rate in all states (that is, the probability of termination of the state conditional on its survival up to this point) must first be defined. Conditional on the model, when the individual is unemployed the hazard rate is:

$$h_u = \lambda_u(1 - G(w^*)) = \lambda_u \tilde{G}(w^*)$$

that is, the probability that an acceptable offer arrives. On the other hand, and again conditional on the model, when the individual is employed the hazard rate is:

$$h_e(w) = \lambda_E(1 - G(w)) + \lambda_R + \eta = \lambda_E \tilde{G}(w) + \lambda_R + \eta$$

or the probability of termination of the current job due to the arrival of an acceptable offer, the occurrence of a reallocation shock or the realization of an involuntary

separation shock. These rates are constant, implying that the density of a complete spell in each state can be characterized by a negative exponential distribution with parameter equal to the hazard rate<sup>13</sup>.

To write the contribution to the likelihood of the durations of unemployment and employment states it is important to be aware that the data can be right censored, that is the end of a particular state is later than the last observed date<sup>14</sup>. In the unemployment state, and given the hazard rate  $h_u$ , the contribution of the unemployment duration to the likelihood for a complete spell and for a right censored spell, respectively, is defined as follows:

$$f_u(t_u) = h_u \exp(-h_u t_u) \quad (3.6)$$

$$f_u(t_u, c_u^r = 1) = \Pr[T > t_u] = \exp(-h_u t_u) \quad (3.7)$$

On the other hand, given the hazard rate  $h_e(w)$  the contributions of the employment duration to the likelihood when the spells are complete, which depends on the conditions of termination of this state, are:

$$f_e(t_k, r_k = 1 | w_k) = h_e(w_k) \exp(-h_e(w_k) t_k) \frac{\lambda_R G(w^*) + \eta}{h_e(w_k)} \quad (3.8)$$

$$f_e(t_k, w_{k+1} > w_k | w_k) = h_e(w_k) \exp(-h_e(w_k) t_k) \frac{(\lambda_R + \lambda_E) \tilde{G}(w_k)}{h_e(w_k)} \quad (3.9)$$

$$f_e(t_k, w_{k+1} < w_k | w_k) = h_e(w_k) \exp(-h_e(w_k) t_k) \frac{\lambda_R [G(w_k) - G(w^*)]}{h_e(w_k)} \quad (3.10)$$

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<sup>13</sup>This is  $f(t) = h \exp(-ht)$  for  $t > 0$ .

<sup>14</sup>The estimation does not correct for left censored spells because they represent only a small number of observations (see Table 3.2). Cycles with double censored spells, on the other hand, are ignored because of an identification problem. As is noted by [Flinn, 2002a], when there are events in which an individual is continuously unemployed, the parameters of the model are not identified since permanent unemployment can be produced by  $\lambda_U = 0$ ,  $\eta = 1$ ,  $b = 1$  or by any combination of these conditions. Fortunately these observations consisted only of 1.9% of the sample.

In equation (3.8) the density of duration is adjusted by the probability of transit to unemployment (due to the arrival of a reallocation shock or an involuntary separation shock) conditional on leaving from a job with wage  $w_K$ . In equation (3.9) the adjustment is made with the probability of leaving to a job with higher wage (due to the arrival of a new job offer or a reallocation shock), and again, conditional on leaving from a job with wage  $w_K$ . Finally, in equation (3.10) the adjustment is incorporated with the probability of leaving to a job with lower wage (which can occur only if a reallocation shock, that does not terminate in unemployment, is realized). It is important to note that each contribution in equations (3.8) to (3.10) is conditional on the wage of the current spell. Finally, with right-censored spells we have the following contribution of the employment duration to the likelihood (in this case, the condition of termination is unknown):

$$f_e(t_k, c_k^r = 1 | w_k) = \exp(-h_e(w_k)t_k) \quad (3.11)$$

To define the contribution of wages to the likelihood it is important to take into account that accepted wages are observed in the data. Conditional in the model, that is using the decision rules in (3.1), it is possible to write the contributions of accepted wages in each state of the cycle as:

$$f_w(w_u) = \frac{g(w_u)}{\tilde{G}(w^*)} \quad (3.12)$$

$$f_w(w_{k+1}, w_{k+1} > w_k | w_k) = \frac{g(w_{k+1})}{\tilde{G}(w_k)} \frac{(\lambda_E + \lambda_R)\tilde{G}(w_k)}{\lambda_E\tilde{G}(w_k) + \lambda_R\tilde{G}(w^*)} \quad (3.13)$$

$$f_w(w_{k+1}, w_{k+1} < w_k | w_k) = \frac{g(w_{k+1})}{\tilde{G}(w^*)} \frac{\lambda_R(G(w_k) - G(w^*))}{\lambda_E\tilde{G}(w_k) + \lambda_R\tilde{G}(w^*)} \quad (3.14)$$

where  $g(\cdot)$  and  $G(\cdot)$  are the p.d.f. and c.d.f. functions, respectively. Equation (3.12) is simply the density of an acceptable offer when leaving the unemployment state (that is, it is a truncation of the wage density at the reservation wage  $w^*$ ). On the

other hand, in equations (3.13) and (3.14) information on the behavior of wages, when job to job transition are observed, is incorporated because both cases have different implications in terms of the model. In equation (3.13) the joint density of observing  $w_{k+1}$  and a wage growth is the density of wages  $g(w_{k+1})$  truncated at the current wage  $w_k$  times the probability of observing a wage growth (after receiving a new offer or a reallocation shock) conditional on leaving that job. Equation (3.14) has a similar interpretation but with a wage cut.

The model incorporates a reallocation shock to empirically account for job to job transition with wage cuts. However, given the self-reported and retrospective nature of the data, it is highly likely that wages are measured with error<sup>15</sup>. If wages are measured with error, the observed wage is  $w^o = w\varepsilon$  where the measurement error  $\varepsilon$  has a c.d.f.  $Q(\varepsilon)$  and p.d.f.  $q(\varepsilon)$  [see, for example, Wolpin, 1987, van den Berg and Ridder, 1998]. The c.d.f. of the observed wage is, therefore,  $Q(\frac{w^o}{w})$  which means that the density of the observed wages takes the form of  $\frac{1}{w}q(\frac{w^o}{w})$ . The question that arises at this point is how to differentiate a wage cut due to a reallocation shock and to measurement error. To isolate this question, the probability of a wage growth in terms of the observed wages is first defined:

$$P(w_{k+1} > w_k) = \phi(w_k^o, w_{k+1}^o) = P\left(\frac{\varepsilon_k}{\varepsilon_{k+1}} > \frac{w_k^o}{w_{k+1}^o}\right) \quad (3.15)$$

The bigger the difference between two consecutive observed wages the higher the probability of observing a change in true wages (this works in both directions with  $P(w_{k+1} > w_k) = \phi(w_k^o, w_{k+1}^o)$  and  $P(w_{k+1} < w_k) = 1 - \phi(w_k^o, w_{k+1}^o)$ ). This implies that smaller changes in observed wages are considered as measurement error. It is now possible to write the density of the observed wages by integrating over the support of

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<sup>15</sup>As is common in the literature, it is assumed that measurement error is present in wage data but not in duration data [Eckstein and van den Berg, 2007, Flinn, 2006].

the (true) accepted wages:

$$\begin{aligned}
f_w(w_u^o) &= \int_{w^*} \frac{1}{w_u} q\left(\frac{w_u^o}{w_u}\right) f_w(w_u) dw_u \\
f_w(w_{k+1}^o | w_k) &= \phi(w_k^o, w_{k+1}^o) \int_{w_k} \frac{1}{w_{k+1}} q\left(\frac{w_{k+1}^o}{w_{k+1}}\right) f_w(w_{k+1}, w_{k+1} > w_k | w_k) dw_{k+1} \\
&\quad + (1 - \phi(w_k^o, w_{k+1}^o)) \int_{w^*} \frac{1}{w_{k+1}} q\left(\frac{w_{k+1}^o}{w_{k+1}}\right) f_w(w_{k+1}, w_{k+1} < w_k | w_k) dw_{k+1}
\end{aligned}$$

Due to space considerations the full likelihood function, using all the elements presented in this subsection, is presented in Appendix B.2<sup>16</sup>. Here however, as illustration, two examples are presented. First, the individual likelihood of a cycle that starts in unemployment, has no right censored duration in unemployment but has right censored duration in the first job is defined as:

$$L(\chi = 1, c_u = 0, c_1 = 1) = f_u(t_u) \int_{w^*} f_e(t_1, c_1 = 1 | w_u) \frac{1}{w_u} q\left(\frac{w_u^o}{w_u}\right) f_w(w_u) dw_u$$

The second example is related with the individual likelihood of a cycle that starts in unemployment, has no right censored duration in the unemployment spell and in the first and second jobs, and terminates in unemployment after the second job (complete cycle):

$$\begin{aligned}
L(\chi = 1, c_u = 0, c_1 = 0, r_1 = 0, c_2 = 0, r_2 = 1) = \\
\phi(w_u^o, w_2^o) \left[ \begin{array}{l} f_u(t_u) \int_{w^*} f_e(t_1, w_2 > w_u | w_u) \frac{1}{w_u} q\left(\frac{w_u^o}{w_u}\right) f_w(w_u) \\ \int_{w_2} f_e(t_2, r_2 = 1 | w_2) \frac{1}{w_2} q\left(\frac{w_2^o}{w_2}\right) f_w(w_2, w_2 > w_u | w_u) dw_2 dw_u \end{array} \right] \\
+(1 - \phi(w_u^o, w_2^o)) \left[ \begin{array}{l} f_u(t_u) \int_{w^*} f_e(t_1, w_2 < w_u | w_u) \frac{1}{w_u} q\left(\frac{w_u^o}{w_u}\right) f_w(w_u) \\ \int_{w_2} f_e(t_2, r_2 = 1 | w_2) \frac{1}{w_2} q\left(\frac{w_2^o}{w_2}\right) f_w(w_2, w_2 < w_u | w_u) dw_2 dw_u \end{array} \right]
\end{aligned}$$

In the estimation two standard assumptions are made. First,  $G(\cdot)$  is a log-normal probability distribution function with parameters  $(\mu, \sigma)$  and second,  $Q(\cdot)$

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<sup>16</sup>As in Flinn [2002a] and Flabbi and Leonardi [2010] only two consecutive jobs are used as a job to job transition because when the number of transitions grows the likelihood becomes rapidly intractable.

is a lognormal probability distribution function with parameters  $(\mu_\varepsilon, \sqrt{-2\mu_\varepsilon})$ <sup>17</sup>. These two assumptions imply that  $(w_k^o, w_{k+1}^o)$  are jointly lognormal, which makes the computation of  $\phi(w_k^o, w_{k+1}^o)$  easier. Finally, it is important to mention that all the parameters in the model are identified<sup>18</sup>. The identification strategy relies on, and is extensively discussed in, Flinn and Heckman [1982] (recoverability conditions and unemployment-employment transitions), Flinn [2002a] (job-to-job transitions) and Flabbi and Leonardi [2010] (job-to-job transition with wage cuts).

### 3.5 RESULTS

#### 3.5.1 ESTIMATION RESULTS

Table 3.3 presents the maximum likelihood estimates of the model parameters  $(\lambda_U, \lambda_E, \lambda_R, \eta, \mu, \sigma, \mu_\varepsilon, b)$  and the reservation wage  $w^*$  for all workers (first column) and separately for skilled and unskilled workers (second and third columns, respectively). The estimation, when all workers are pooled together, hides important differences in the dynamics of the labor market by education level. As expected, this is particularly true for the parameters that govern the wage distributions and for the reservation wages. Also, it is observed that the arrival rate of the reallocation shock,  $\lambda_R$ , is virtually zero for all samples, which means that the observed wage cuts are small enough so they are absorbed by the measurement error instead of representing drops in the true wages<sup>19</sup>.

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<sup>17</sup>This is a consequence of two assumption (1)  $E(\varepsilon|w) = 1$  and (2) lognormality.

<sup>18</sup>Parameters  $\rho$  and  $b$  cannot be identified separately, but if a value of  $\rho$  is assumed then  $b$  can be recovered from equation (3.4). In the particular case analyzed,  $\rho$  is defined as 0.065 in annualized terms [see, for example, Fuenzalida and Mongrut, 2010].

<sup>19</sup>The model without measurement error was also estimated but the fit of the model with measurement error was better in terms of matching the level and the dispersion of the cross-section wage distribution. These estimates are available by request.



The estimates of the arrival rates of job offers while unemployed  $\lambda_U$  imply that workers should on average expect offers every 11 months. This implies that it takes time to leave the unemployment state. This phenomena is more pronounced for the skilled worker because they should expect offers almost every 15 month (compared with slightly less than 11 months for unskilled workers). This result is qualitatively different from the findings of Flabbi and Leonardi [2010] for the U.S. economy and could indicate that in the Chilean labor market for skilled workers is tighter. On the other hand, the arrival rate of offers while on the job,  $\lambda_E$ , indicate that new job opportunities do not arrive often in the Chilean labor market. In particular, an employee should expect the arrival of new job opportunities every 9 years, on average. It is also observed that, compared with skilled workers, the unskilled workers are less fortunate in receiving job offers while on the job. Indeed, job opportunities arrive on average every 7 and 12 years for skilled and unskilled workers, respectively. Estimates of the arrival rates of involuntary separations,  $\eta$ , in turn, indicates that it is not common to observe termination due to this type of shock because it takes, on average, more than 50 years to receive an involuntary separation shock for all samples. The findings for  $\lambda_E$  and  $\eta$  combined indicate that jobs are very persistent in the Chilean labor market. This result is consistent with Huneus and Repetto [2005] findings.

The reservation wage in the Chilean labor market is 1.1 U.S. dollar per hour. As was mention before, this figure hides important differences by education level. In particular, the reservation wage for skilled workers is 3.5 U.S. dollars per hour, while for unskilled workers it is 0.7 U.S. dollars per hour. Hence, skilled workers request a wage that is 5 times the wage requested by unskilled workers in order to accept a job while unemployed. The estimates of the parameters that govern the wage distribution, that is  $\mu$  and  $\sigma$ , imply an average offered wage of 2.3 U.S. dollar per hour, this average being 4.6 and 1.8 U.S. dollars per hour for skilled and unskilled

workers, respectively. Therefore, skilled workers earn on average more than twice that earned by unskilled workers. On the other hand, the standard deviations of wages is around 0.45 U.S. dollar per hour with almost no difference across education level. The values of the estimates for the reservation wage and for the parameters of the wages distribution imply that the average accepted wages are on an order of magnitude similar to the average offered wages for all samples. Finally, mention about the estimates of the measurement error distribution parameters is pertinent. The distribution of the measurement error is more dispersed for skilled workers (recall that  $\sigma_\varepsilon = \sqrt{-2\mu_\varepsilon}$ ) indicating that bigger measurement errors are more likely in the observed wages of this group of workers.

### 3.5.2 CROSS-SECTION VS. LIFETIME INEQUALITY

In order to generate lifetime inequality indices, it is necessary first to construct measures of long-run welfare. To achieve that goal a simulation method was used. In particular, using the point estimated parameters in Table 3.3, the model was simulated to construct labor market careers of 45 years for 10,000 individuals as in Flinn [2002a]. To preserve the relative weights of the composition between the groups with different education levels, 21% of those individuals were simulated using the skilled worker estimated parameters while the rest were simulated using the estimated parameters of the unskilled workers. In the simulation each individual started its career in the unemployment state<sup>20</sup> and in each period a wage and duration were drawn from the appropriate distributions. In the case of the former, a lognormal distribution truncated at the reservation wage or at the current wage, depending on the type of transition, was used, while in the case of the latter the relevant distribution was the exponential distribution. Once the careers were simulated, the long-run (or lifetime)

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<sup>20</sup>This can be interpreted as an individual looking for a job for the first time.

welfare for an individual  $i$  was calculated as the sum of the discounted value of his labor income in each state [Flabbi and Leonardi, 2010], that is:

$$LW_i = \sum_{j=1}^J \exp(-\rho t_j) \int_{t_j}^{t_{j+1}} y_{ij} \exp(-\rho v) dv \quad (3.16)$$

where  $y_{ij} = b$  if the spell  $j$  is unemployment,  $y_{ij} = w_{ij}$  if the spell  $j$  is employment,  $t_j$  is the duration of the spell  $j$  and  $J$  is the total number of spells (note that  $\sum_{j=1}^J t_j = 540$  months). In equation 3.16 each flow income in the career is discounted to the beginning of the spell for which it was valid and then all these discounted values were again discounted to the beginning of the period. It is important to mention that the first unemployment spell was dropped because it violates the steady state condition of the flows of the labor market (all the individuals are unemployed).

In addition to the construction of the lifetime welfare measures, a distribution of cross-section measure of labor incomes can also be extracted from the simulations. This is particularly useful to asses the fit of the model in matching moments of that distribution with those observed in the data<sup>21</sup>. The cross-section measure of labor incomes is just the average hourly wage in the 11<sup>th</sup> year of the career. Like in Flinn [2002a] and Flabbi and Leonardi [2010], the Generalized Entropy classes of inequality indices are used to judge the degree of inequality in both the cross-section measure of labor income and the lifetime measure welfare. The Generalized Entropy inequality

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<sup>21</sup>In order to compare this generated cross-section distribution with the observed in the data, the former has to be adjusted to include the measurement error. This can be done generating random numbers from a lognormal distribution using the parameters estimated in Table 3.3 for the measurement error.

index with parameter  $\alpha$  is defined by<sup>22</sup>:

$$GE(\alpha) = \frac{1}{\alpha(\alpha - 1)} \left[ \frac{1}{N} \sum_{i=1}^N \left( \frac{y_i}{\bar{y}} \right)^\alpha - 1 \right] \quad (3.17)$$

Given the important difference in the labor market dynamics by level of education, it is also useful to decompose the inequality indices to see if the overall inequality reflect differences within skill groups or differences between skill groups. The decomposition used is the following [Jenkins and Van Kerm, 2011]:

$$GE(\alpha) = GE^B(\alpha) + GE^W(\alpha) \quad (3.18)$$

The within-group inequality can be calculated for  $M$  subgroups as follows:

$$GE^W(\alpha) = \sum_{m=1}^M \theta_m^\alpha \psi_m^{1-\alpha} GE_m(\alpha) \quad (3.19)$$

where  $\theta_m$  is subgroup  $m$ 's share of total income,  $\psi_m$  is  $m$ 's population share, and  $GE_m(\alpha)$  is the inequality within group  $m$ . Between-group inequality,  $GE^B(\alpha)$ , can be calculated by imputing the mean income of each subgroup to all the individuals in that subgroup.

Table 3.4 shows the inequality indices, for  $\alpha = 0, 1, 2$ , calculated using the lifetime welfare measures (upper panel), the simulated cross-section earnings (middle panel) and a cross-section of earnings extracted from the data (lower panel). In each panel the decomposition described above by education level is also presented. Before discussing the findings in lifetime inequality, a discussion about the extent to which the model is able to replicate the data in the cross-section is necessary. Comparing the middle with

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<sup>22</sup>As Cowell [2000] mentions, any measure of inequality should satisfy (1) Anonymity (the metric does not depend on who is the individual), (2) Scale independence (the metric is independent of the aggregate level of income), (3) Population independence (the metric does not depend on the size of the population), and (4) Transfer principle (the metric has to decrease if there are transfers from rich to poor agents). The Generalized Entropy inequality indices satisfy these axioms.

the lower panels of Table 3.4, it is evident that the model tends to overestimate the level of inequality and this occurs not only with the total sample but also by skill level. The difference also becomes higher when more weight is given to the differences in income shares among the rich (that is  $\alpha$  if higher). For this reason, the estimates with lower values of  $\alpha$  will receive more weight in the conclusions. On the other hand, the model is successful in preserving the inequality ordering observed in the data, that is, the inequality tends to be higher for the skilled workers; and the source of inequality, for both skilled and unskilled workers, is primarily differences in earnings within groups. The model also delivers relatively close estimates of the average earnings for all samples and by skill level.

The estimates of lifetime inequality, in the upper panel of Table 3.4, indicates that inequality in the Chilean labor market is not only high at the cross-section level but also from a lifetime perspective. Even though these estimates can be slightly overestimating the true level of inequality, given the discussion in the previous paragraph, it is still high. This is reinforced by the fact that the lifetime inequality estimates use the true earnings instead of the earnings measured with error as in the case of the cross-section inequality measures (the measurement error introduces more variance to the data). As in the cross-section inequality case, lifetime welfare of skilled workers tends to be more unequal when compared with their unskilled counterparts. Also, the primary source of inequality is differences within skilled groups. Finally, the estimates indicate that an average worker in Chile has a lifetime welfare (in this case also earnings) of 25 U.S. dollars per hour, with 35 and 16 U.S. dollars per hour for skilled and unskilled workers, respectively.

## 3.6 EXPERIMENTS

In this section three experiments were performed in order to closely analyze the sources of the lifetime inequality in the Chilean labor market. First, the lifetime inequality indices are decomposed into two sources, mobility and distribution, to isolate which source has more impact in the total index. Second, the marginal effect on lifetime inequality of each individual parameter is analyzed to find out which parameter or group of parameters, within the mobility and distribution sources, has more impact in the inequality indices. Finally, the effect of age is analyzed by estimating the model with different age groups.

### 3.6.1 LIFETIME INEQUALITY DECOMPOSITION

To decompose the lifetime inequality measures, into inequality due to mobility and inequality due to wage distribution, it is necessary to have a labor market with lower lifetime inequality for comparison purposes (a benchmark). There are two alternatives. The first is to generate a fictitious economy by simply setting the parameters and using that economy as a baseline. The second, and empirically more interesting, is to use a real labor market as a baseline. The question, however, is what labor market is the best to choose. This chapter applies this second approach and uses the United States as the benchmark economy. Three reasons are behind this choice. First, this economy has one of the less regulated labor markets worldwide (see figure 3.1). Considering the differences in the level of regulation in the labor market between Chile and the United States, it will be possible to draw some conclusions regarding the relationship between lifetime inequality and labor market regulation. Second, lifetime inequality measures are lower for this country. Finally, there are comparable estimates, in terms

of the model and the sample characteristics, in the literature [Flinn, 2002a, Flabbi and Leonardi, 2010, are the obvious choices].

The decomposition was performed in the following way. Two questions were asked. First, what would happen if the Chilean economy had the same mobility in the labor market as the United States maintaining the features of the wage distribution? Let this be the mobility effect. In this case, the model was simulated with the parameters  $\lambda_U$ ,  $\lambda_E$  and  $\eta$  for the United States and the parameters  $\mu$ ,  $\sigma$  and  $b$  for Chile<sup>23</sup>. Second, what would happen if the Chilean economy had the same wage distribution as the United States while maintaining its mobility level. Let this be the distribution effect. In this case, the model was simulated with the parameters  $\lambda_U$ ,  $\lambda_E$ ,  $\eta$ , and  $b$  for Chile and the parameters  $\mu$ ,  $\sigma$  for the United States. Note that each simulation takes into account all the equilibrium effects of changes in the parameters, that is in each simulation a new reservation wage was found given the new parameters. To analyze quantitatively the importance of these two effects, and following Flabbi and Leonardi [2010], the proportion of the difference in the lifetime inequality index explained by the experiment was calculated, that is:

$$\Delta(\alpha)^{Experiment} = \frac{GE(\alpha)^{CH} - GE(\alpha)^{Experiment}}{GE(\alpha)^{CH} - GE(\alpha)^{US}} \quad (3.20)$$

The inequality indices for the United States were calculated using the simulated careers approach described in section 3.5 with the parameters estimated by Flinn [2002a]<sup>24</sup>. The results of this decomposition are presented in Table 3.5. The upper panel presents the inequality indices generated with the different combination of

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<sup>23</sup>Given the estimates presented in Table 3.2, the reallocation rate  $\lambda_R$  was set to zero.

<sup>24</sup>This choice is based only on the differences in lifetime inequality estimates in both countries. The estimates of Flinn [2002a] generates lifetime inequality measures that are lower than the estimates of Flabbi and Leonardi [2010] for the United States. Since the goal of this chapter is to compare the Chilean economy with an economy that has very different levels of lifetime inequality, the estimates that generate the bigger differences were chosen.

parameters while the lower panel presents the proportions calculated using equation 3.20.

It can be noticed, comparing the upper panels of Table 3.4 and Table 3.5, that changing the mobility (in this case increasing it) reduces the level of lifetime inequality substantially. Even though this result is observed for both skilled and unskilled workers, the reduction in the level of inequality is more pronounced for the first group. Additionally, a more mobile labor market also changes the main source of inequality to between groups differences in income. Changing the wage distribution, on the contrary, tends to increase the levels of lifetime inequality. This result is more pronounced for the skilled workers and exacerbates the differences within the skilled group. Lifetime inequality increases, in this case, because even though the average wage in the experiment is higher so is the variance. Clearly, the variance effect dominates, increasing the dispersion of earnings in the lifetime perspective. In quantitative terms, the lower panel of Table 3.5 shows that the reduction in lifetime inequality due to mobility is higher relative to the difference in the lifetime inequality between countries, for both skilled and unskilled workers (at least 6.6% higher). This is not the case for the overall inequality, for which the reduction is only 75% of the between countries difference in inequality. On the other hand, the increase in inequality due to the wage distribution is at most 58% of the difference in the inequality index between countries.

This counterfactual experiment indicates that the main source of lifetime inequality in the Chilean labor market, regardless of the education level, is the lack of mobility (relative to the United States labor market). The results show that, in quantitative terms, the effect is not negligible at all. Considering the differences in labor market regulation between Chile and the United States, the last result provides additional empirical evidence in favor of a positive relationship between regulation



and inequality, that is a less regulated labor market has more mobility, and therefore less lifetime inequality<sup>25</sup>.

### 3.6.2 MARGINAL EFFECT OF INDIVIDUAL PARAMETERS ON LIFETIME INEQUALITY

The same simulation approach was used to find the marginal effect of each individual parameter on the lifetime inequality measures. In particular, the model was simulated to create careers changing one parameter in a range of  $\pm 25\%$  while keeping the rest of the parameters at their point estimates. This was done by skill level and the inequality indices,  $G(\alpha)$  for  $\alpha = 0, 1, 2$ , were calculated with the resulting welfare measures. For example, to find the marginal effect of  $\lambda_U$ , for the case of skilled workers, simulations were performed with different values of this parameter in the range of 0.050 and 0.085 while maintaining the other parameters in the estimates (second column) of Table 3.3. As before, the arrival rate of reallocation shocks was set to zero.

The results are shown in figures 3.4 and 3.5 for skilled and unskilled workers, respectively. In the case of skilled workers (figure 3.4), it is evident that the parameter with the greatest impact on the lifetime inequality measures is the arrival rate of job offers while unemployed. In particular, the faster the workers leave the unemployment state, the lower is the lifetime inequality. While on the job, on the other hand, the impact of the arrival rates of job opportunities and involuntary separation shocks is in the same direction of the previous arrival rate, but the size of the impact is by far smaller in these cases. In terms of the distribution parameters, an increase in the mean of the logarithm of wages tends to reduce lifetime inequality and this

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<sup>25</sup>This result is consistent with Heckman and Pages [2000] findings for Latin American countries. Their results suggest that labor market regulations are an inequality-increasing mechanism. In particular, less-stringent job security tends to be associated with higher turnover and greater flexibility in the labor market.

relationship seems to be nonlinear. In the case of the variance of the logarithm of wages the direction of the effect is not clear.

In the case of unskilled workers (figure 3.5), it is observed that the results with respect to the mobility parameters are very similar to those observed for skilled workers. The only exception is the arrival rate of the involuntary separation shocks, for which the direction of the impact on lifetime inequality is not clear. With respect to the distribution parameters, the results are the opposite to those found for skilled workers. In particular, while the impact of the mean of the logarithm of wages is not clear, the variance of the logarithm tend to increase lifetime inequality measures. These results, namely a negative marginal effect of mobility parameters on lifetime inequality and an unclear direction of the marginal effect of the distribution parameters on lifetime inequality, reinforce what was found in the decomposition previously discussed.

### 3.6.3 LABOR MARKET MOBILITY BY AGE

The main result of the decomposition described early in this section was that the lack of mobility is the primary source of lifetime inequality. This subsection tries to go further and analyzes the age dimension of the mobility in the Chilean labor market. This is important because Sapelli [2011], in his extensive analysis of inequality in Chile, finds that changes in cross-section income distribution has been favorable for the younger workers. This exercise seeks to verify this hypothesis in the lifetime dimension. To fulfill this goal, the observed heterogeneity in terms of age is exploited in the estimation of the model. In particular, the model was re-estimated by skill level allowing the arrival rates to vary with different ages while restricting the remaining

parameters to be equal across ages<sup>26</sup>. It is assumed that the arrival rates vary with the age groups in a very simple and linear fashion:

$$\lambda_U = \beta_{1,\lambda_U}D_1 + \beta_{2,\lambda_U}D_2 + \beta_{3,\lambda_U}D_3 \quad (3.21)$$

$$\lambda_E = \beta_{1,\lambda_E}D_1 + \beta_{2,\lambda_E}D_2 + \beta_{3,\lambda_E}D_3 \quad (3.22)$$

$$\eta = \beta_{1,\eta}D_1 + \beta_{2,\eta}D_2 + \beta_{3,\eta}D_3 \quad (3.23)$$

where  $D_1$  is an indicator variable which is equal to 1 if the individual was born between 1971 and 1986 (that is, he was 20-35 years old in 2006) and zero otherwise,  $D_2$  is an indicator variable which is equal to 1 if the individual was born between 1961 and 1970 (that is, he was 36-45 years old in 2006) and zero otherwise, and finally,  $D_3$  is an indicator variable which is equal to 1 if the individual was born between 1941 and 1960 (that is, he was 46-65 years old in 2006) and zero otherwise. In this formulation the parameter  $\beta_{i,j}$  represents itself, the arrival rate of the shock  $j$  for the age group  $i$ .

Figures 3.6 and 3.7 graphically present the estimated arrival rate for each shock by age groups and a 95% confidence interval for skilled and unskilled workers, respectively. In the case of the skilled workers (figure 3.6), there are statistically significant differences in all arrival rates between the younger group ( $D_1$ ) and the older group ( $D_3$ ). Unemployed younger workers receive offers almost five times faster than the older workers, which means that the first group leaves the unemployment state faster. On the other hand, when on the job young workers receive new job opportunities more than twice as fast as the older workers. Finally, termination due to involuntary separation is three times more frequent for younger workers compared with the older workers. These last two results indicate that jobs are more persistent for older workers. For the unskilled workers (figure 3.7), the results are similar, namely

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<sup>26</sup>The model was not estimated as a segmented market by age because of sample size restrictions. The estimates are available upon request.

there are statistically significant differences in the arrival rates between the younger group and the older group and the magnitudes of these differences are similar to those found for the skilled workers. The main exception is the arrival rate while unemployed where the difference is not as pronounced as in the case of the skilled workers (less than twice). These results and the relation between mobility and lifetime inequality indicate that Sapelli [2011] findings also hold in the lifetime perspective.

Comparing skilled and unskilled workers, the results indicate that offers while unemployed arrive at similar rates for young workers, while for older workers the unskilled group receives their offers three times faster than their skilled counterparts. On the other hand, while on the job unskilled workers receive new job opportunities more often than skilled workers, regardless of the age (the difference is 1.5 times). Finally, unskilled workers experience involuntary separation shocks three times more often, regardless of the age.

### 3.7 CONCLUDING REMARKS

This chapter structurally estimates a partial equilibrium search model with on-the-job search using data for the Chilean labor market. The model was estimated separately by education level (skilled vs. unskilled workers). Chile was chosen because it has high and persistent levels of cross-section inequality and it has a rich data set with labor market histories. This is crucial because any attempt to judge lifetime inequality requires both transitions from unemployment to employment and job to job transitions. In order to calculate a long-run measure of welfare, the model and the estimated parameters were used to simulate labor market careers. In particular, the discounted value of the labor income along the career was used as measure of welfare. Finally,

the Generalized Entropy family of indices were used to judge the degree of inequality in this measure of welfare.

The estimation results indicate that there are important differences in the dynamics of the labor market by education level. In terms of the transitions across labor market states, the estimated results show that it takes time to leave the unemployment state and this is more pronounced for the skilled worker. On the other hand, new job opportunities do not arrive often in the Chilean labor market and the unskilled workers are less fortunate in receiving job offers while on the job. In turn, involuntary separations are not common to observe. It can be inferred from the last two findings that jobs are very persistent in the Chilean labor market. In terms of the wage distribution, results indicate that skilled workers earn on average more than twice that earned by unskilled workers and that the dispersion in the wage distribution by education level is very similar. Finally, with respect to the reservation wages, it was found that skilled workers request a wage that is 5 times the wage requested by unskilled workers, in order to accept a job while unemployed.

The estimates of lifetime inequality show that inequality in the Chilean labor market is not only high at the cross-section level but also from a lifetime perspective. Also, as in the cross-section perspective, lifetime welfare for skilled workers tends to be more unequal when compared with their unskilled counterparts. The decomposition of the inequality indices by education level, on the other hand, shows that the primary source of inequality is differences within skilled groups. Comparing the parameters of the Chilean labor market with those estimated in the literature for the United States labor market (as a benchmark), the lifetime inequality measures were decomposed into mobility effect and distribution effect. This counterfactual exercise indicates that an increase in the mobility of the Chilean labor market substantially reduces the level of lifetime inequality. This is not the case when the wages distribution is changed.

Both results hold regardless of the skill level. This implies that the main source of lifetime inequality in the Chilean labor market is the lack of mobility (relative to the United States labor market). Additionally, these results provide additional empirical evidence in favor of a positive relationship between regulation and inequality.

To analyze in more detail the effect of each parameter on the lifetime inequality measures, the marginal effect of each individual parameter was constructed using the same simulation approach. The results indicate that the parameter that affects the most the lifetime inequality measures for both skilled and unskilled workers, that is the transition rate from unemployment to employment, is among the mobility parameters . Finally, the model was re-estimated differentiating the mobility rates by age (three groups were used). This was done to verify whether the recent findings in the literature for Chile, regarding less unequal cross-section earnings distribution observed for the young workers, hold also in the lifetime perspective. Results indicate that there are statistically significant differences in the mobility parameters between the younger workers and the older workers. In particular, unemployed younger workers receive job offers more often than the older workers, while unemployed and on the job. Also, termination due to involuntary separation is more frequent for younger workers. From these results it is possible to infer that jobs are more persistent, and therefore higher lifetime inequality should be expected for older workers.

Table 3.1: Descriptive Statistics on Durations (Months)

Event	Skilled			Unskilled		
	Mean	S.D.	% of RC	Mean	S.D.	% of RC
All Cycles						
$t_u$	10.72	22.54	0.04	8.33	20.99	0.06
$t_1$	114.84	73.91	0.67	100.41	78.61	0.55
$t_2$	18.01	13.22	0.12	15.62	12.14	0.12
Cycles Starting in Unemployment State						
$t_u$	10.72	22.54	0.27	8.33	20.99	0.23
$t_1$	12.22	13.42	0.35	9.65	11.26	0.29
$t_2$	12.63	8.78	0.13	12.41	11.18	0.09
Cycles Starting in Employment State						
$t_1$	127.88	68.00	0.73	127.45	69.25	0.65
$t_2$	19.05	13.70	0.12	16.70	12.27	0.13

Note: Left censored spells are as much as 0.6% and 1.6% of the total spells for skilled and unskilled workers, respectively.

Table 3.2: Descriptive Statistics on Wages (U.S. Dollars of 2004)

Event	Skilled			Unskilled		
	Mean	S.D.	% $w_{t+1} > w_t$	Mean	S.D.	% $w_{t+1} > w_t$
All Cycles						
$w_u/w_1$	5.18	3.77	0.85	1.94	0.94	0.82
$w_2$	4.21	2.95	0.16	1.73	0.75	0.18
$w_3$	4.38	2.90		1.81	0.86	
Cycles Starting in Unemployment State						
$w_u$	3.34	2.89	0.66	1.45	0.60	0.69
$w_2$	4.17	2.72	0.18	1.54	0.54	0.17
$w_3$	6.08	4.02		1.65	0.70	
Cycles Starting in Employment State						
$w_1$	5.42	3.80	0.89	2.08	0.98	0.87
$w_2$	4.22	3.00	0.16	1.80	0.79	0.18
$w_3$	4.04	2.55		1.87	0.90	

Notes: The figures, expressed in U.S. dollars of 2004, were calculated using the 2004 average exchange rate: 609.55 *Pesos/US*.

Table 3.3: Maximum Likelihood Estimates

Parameter	All Workers	Skilled Workers	Unskilled Workers
$\lambda_U$	0.08896 (0.00355)	0.06800 (0.00707)	0.09279 (0.00195)
$\lambda_E$	0.00923 (0.00044)	0.01170 (0.00078)	0.00717 (0.00032)
$\lambda_R$	0.00000 (0.00000)	0.00000 (0.00000)	0.00000 (0.00000)
$\eta$	0.00169 (0.00007)	0.00085 (0.00009)	0.00195 (0.00015)
$\mu$	0.79049 (0.01837)	1.53089 (0.06597)	0.54656 (0.02602)
$\sigma$	0.20829 (0.00633)	0.09220 (0.01197)	0.26476 (0.01284)
$w^*$	1.13852 (0.03785)	3.46890 (0.25994)	0.67888 (0.02812)
$\mu_\epsilon$	-0.24523 (0.01039)	-0.30472 (0.03188)	-0.13222 (0.00697)
$b$	-0.0672	2.58990	-0.63440
$E(w)$	2.25282	4.64196	1.78891
$V(w)$	0.22503	0.18395	0.23238
$LogL$	-14993	-2670	-12066
$N$	3265	693	2572

Note: Asymptotic standard errors in parentheses.



Table 3.4: Lifetime vs Cross-Section Inequality Measures

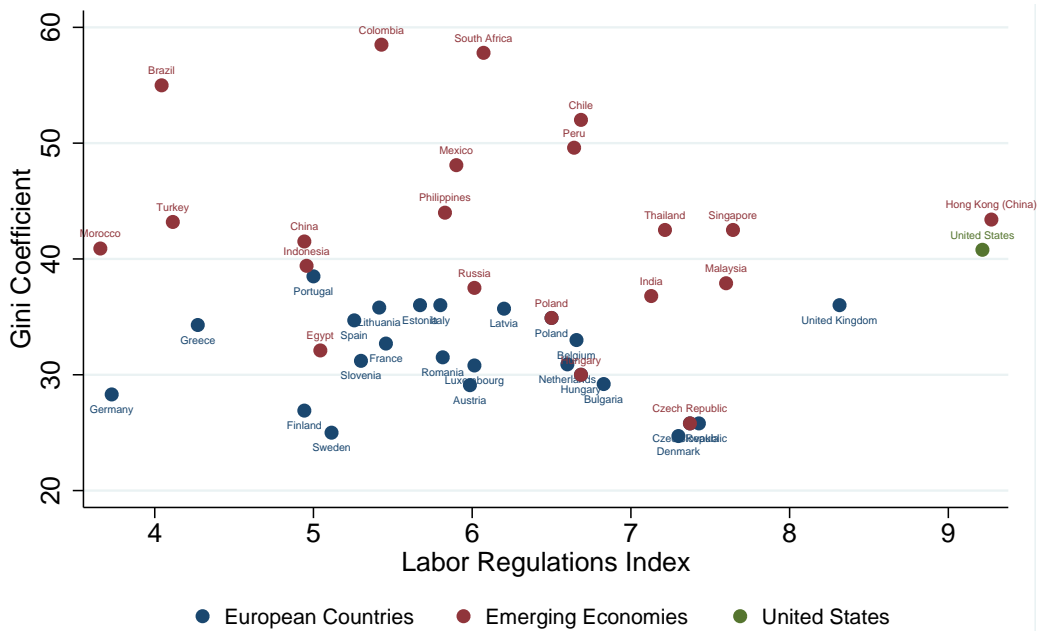
	$n_s/n$	$y$	$GE(0)$	$GE(1)$	$GE(2)$
Lifetime Inequality Measures: Welfare					
Total	1.0000	25.4951	0.2716	0.2269	0.2508
Skilled	0.2125	34.9116	0.3006	0.1925	0.1683
Unskilled	0.7876	16.0787	0.1908	0.1452	0.1370
Within-group Inequality			0.2141	0.1627	0.1773
Between-group Inequality			0.0575	0.0642	0.0736
Cross-Section Inequality Measures: Simulated Earnings					
Total	1.0000	3.3818	0.2866	0.3180	0.5102
Skilled	0.2138	4.8289	0.3085	0.3065	0.4078
Unskilled	0.7862	1.9348	0.1765	0.1709	0.2004
Within-group Inequality			0.2047	0.2257	0.4022
Between-group Inequality			0.0819	0.0923	0.1080
Cross Section Inequality Measures: Observed Earnings					
Total	1.0000	3.6826	0.2253	0.2598	0.3741
Skilled	0.2410	5.3095	0.2308	0.2219	0.2494
Unskilled	0.7590	2.0558	0.0991	0.1009	0.1105
Within-group Inequality			0.1308	0.1554	0.2540
Between-group Inequality			0.0944	0.1044	0.1201

Note: Observed earnings correspond to those observed in June 2004. Simulated earnings are corrected for measurement error to make them comparable with the observed earnings. Lifetime inequality measures are calculated using the true earnings, and therefore do not include the measurement error.

Table 3.5: Lifetime Inequality Measures Decomposition

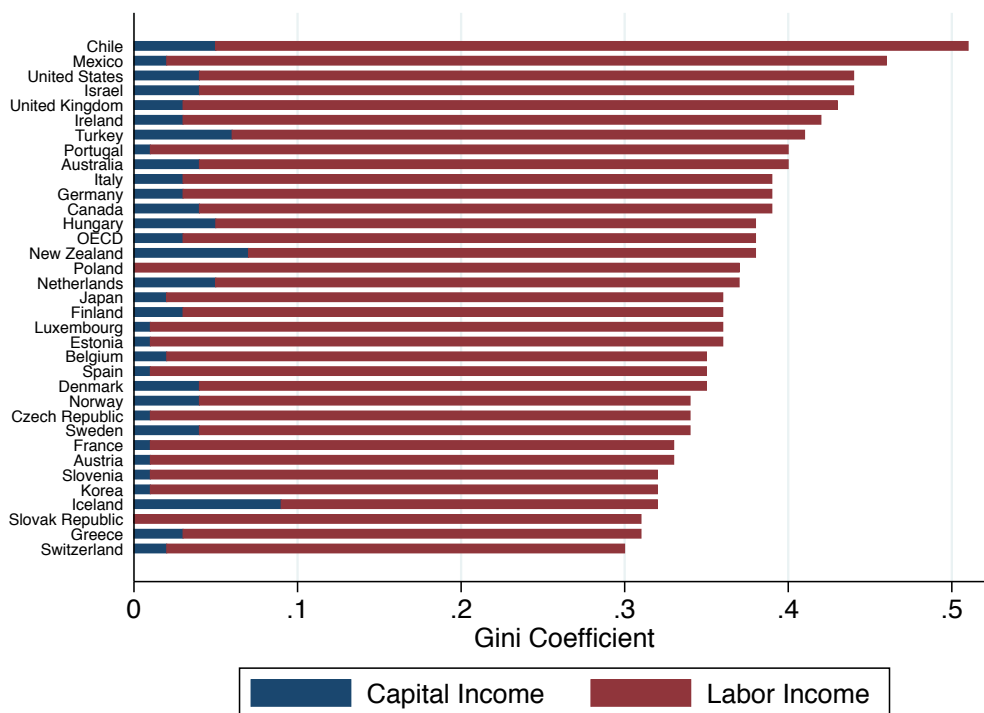
	Index - Mobility			Index - Distribution		
	$GE(0)$	$GE(1)$	$GE(2)$	$GE(0)$	$GE(1)$	$GE(2)$
Total	0.1079	0.1118	0.1261	0.2764	0.2038	0.20373
Skilled	0.0374	0.0323	0.0293	0.3931	0.2507	0.23974
Unskilled	0.0415	0.0388	0.0381	0.2431	0.1875	0.18835
Within-group Inequality	0.0406	0.0363	0.0387	0.2749	0.2023	0.20224
Between-group Inequality	0.0673	0.0755	0.0874	0.0014	0.0015	0.00149
	% Explained - Mobility			% Explained - Distribution		
Total	0.7594	0.6641	0.6370	-0.0219	0.1334	0.2405
Skilled	1.1019	1.1778	1.2401	-0.3871	-0.4278	-0.6374
Unskilled	1.0660	1.1011	1.1308	-0.3733	-0.4367	-0.5877
Within-group Inequality	1.0774	1.1266	1.1043	-0.3775	-0.3529	-0.1991
Between-group Inequality	-0.1804	-0.1857	-0.1964	1.0290	1.0270	1.0246

Figure 3.1: Cross-Section Inequality and Labor Market Structure



Sources: WDI World Bank 1997-2009, IEF Economic Freedom Annual Report 2002-2008

Figure 3.2: Contributions to the Inequality Index of Market Income - Working age population in the late 2000s



Note: Contributions to overall household market income inequality are derived by multiplying the concentration coefficients of each income source by their weight in total market income. The data for Greece, Hungary, Mexico and Turkey are net of taxes. Data for France and Ireland refer to the mid-2000s.

Source: OECD Income Distribution and Poverty, OECD Social Expenditure Statistics (database). Borrowed from OECD's *Economic Policy Reforms: Going for Growth 2012*.

Figure 3.3: Example of an Individual Labor Market History that becomes Two Cycles

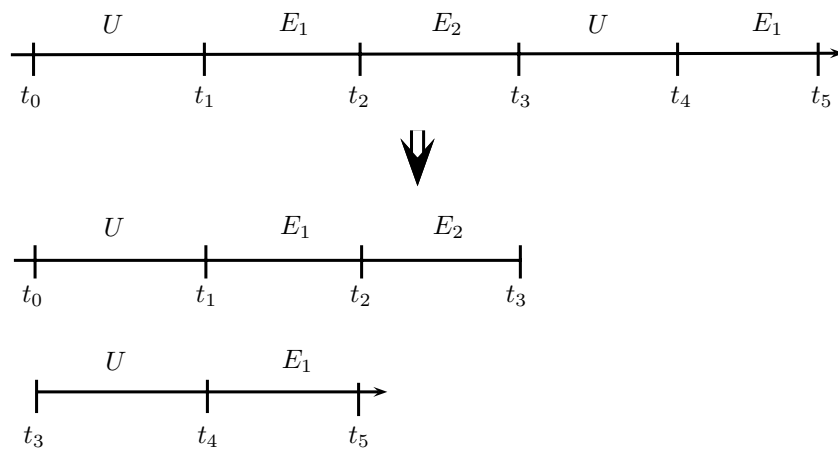
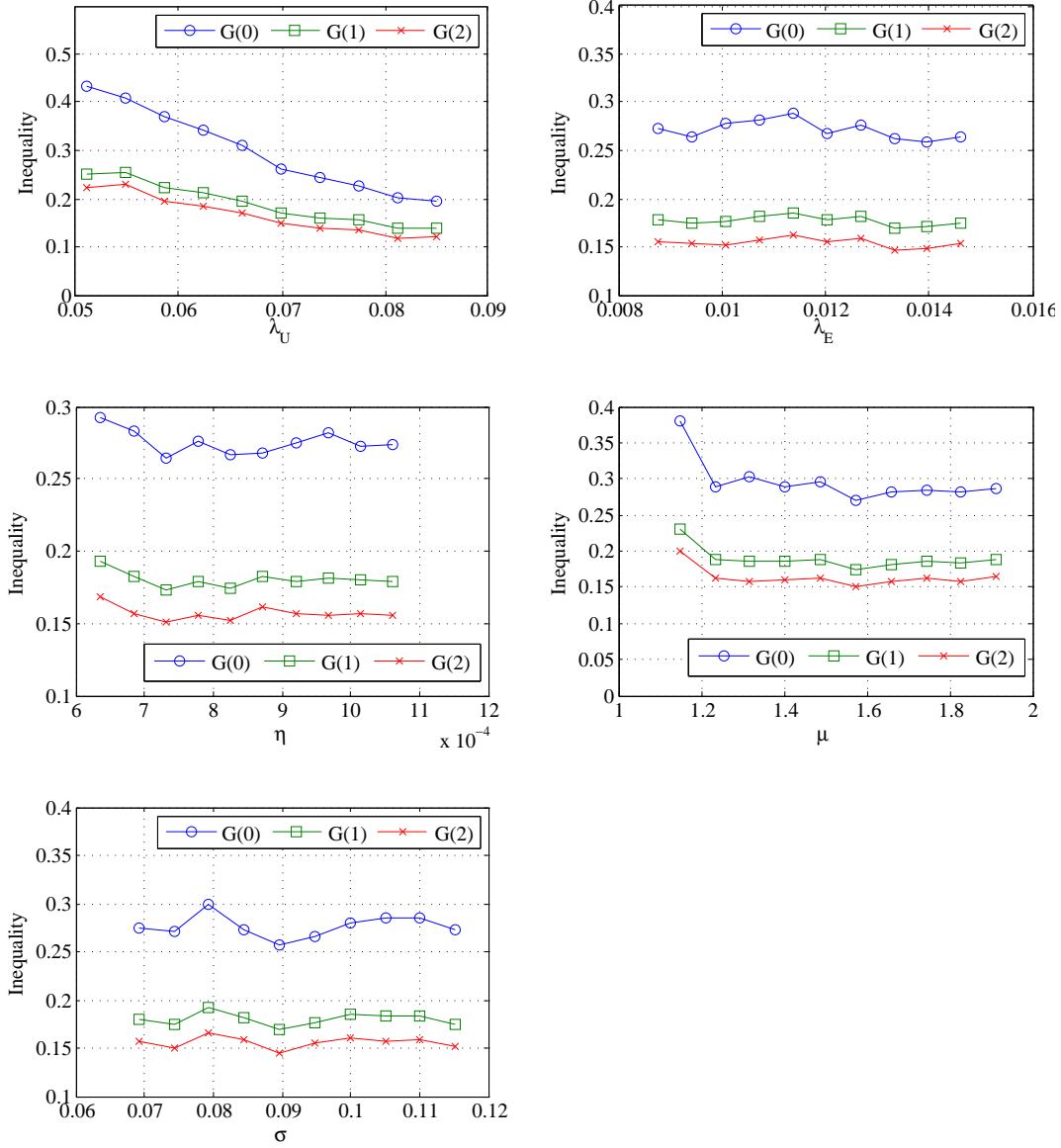
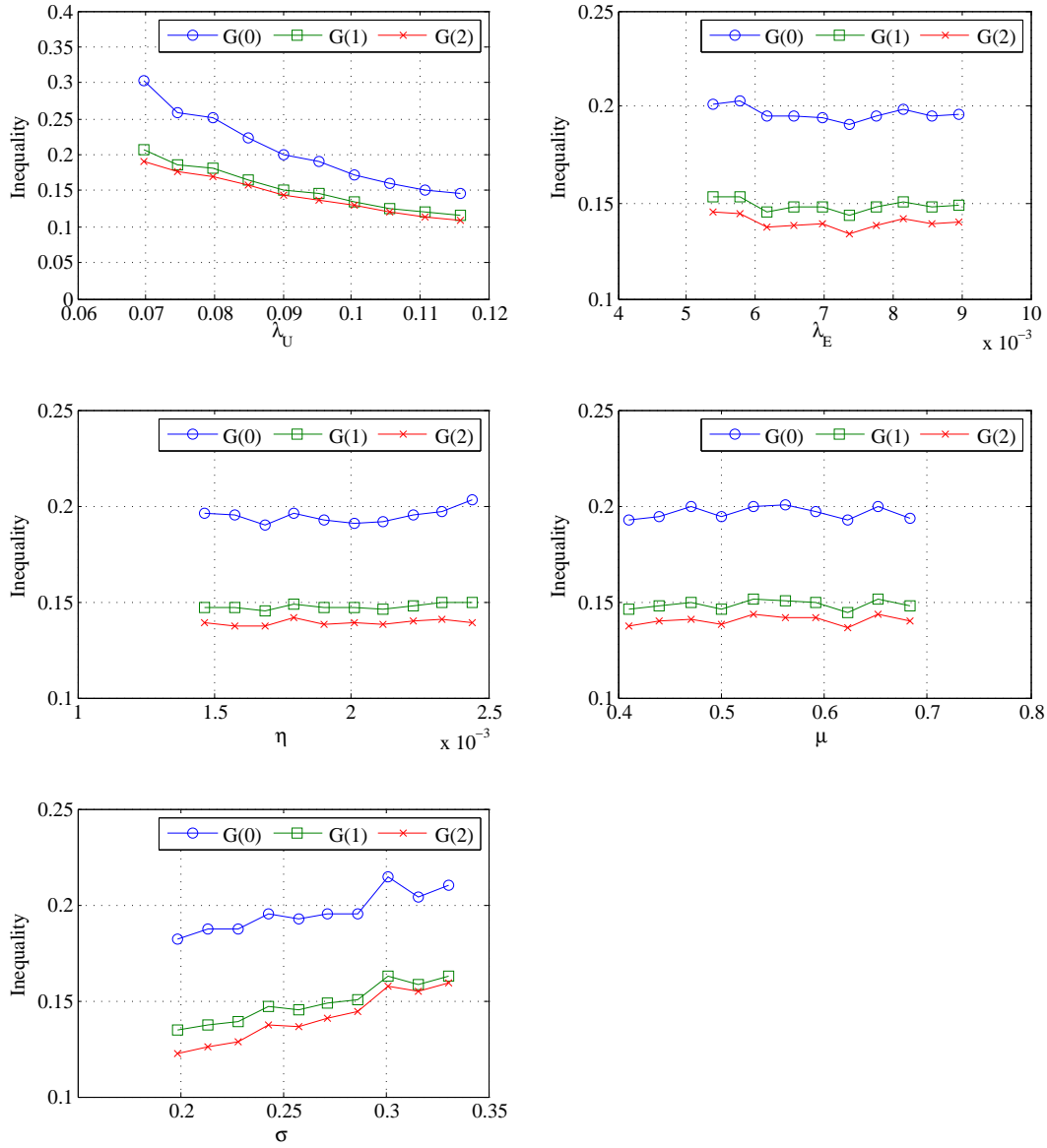


Figure 3.4: Effect of Individual Parameters on Lifetime Inequality Measures - Skilled Workers



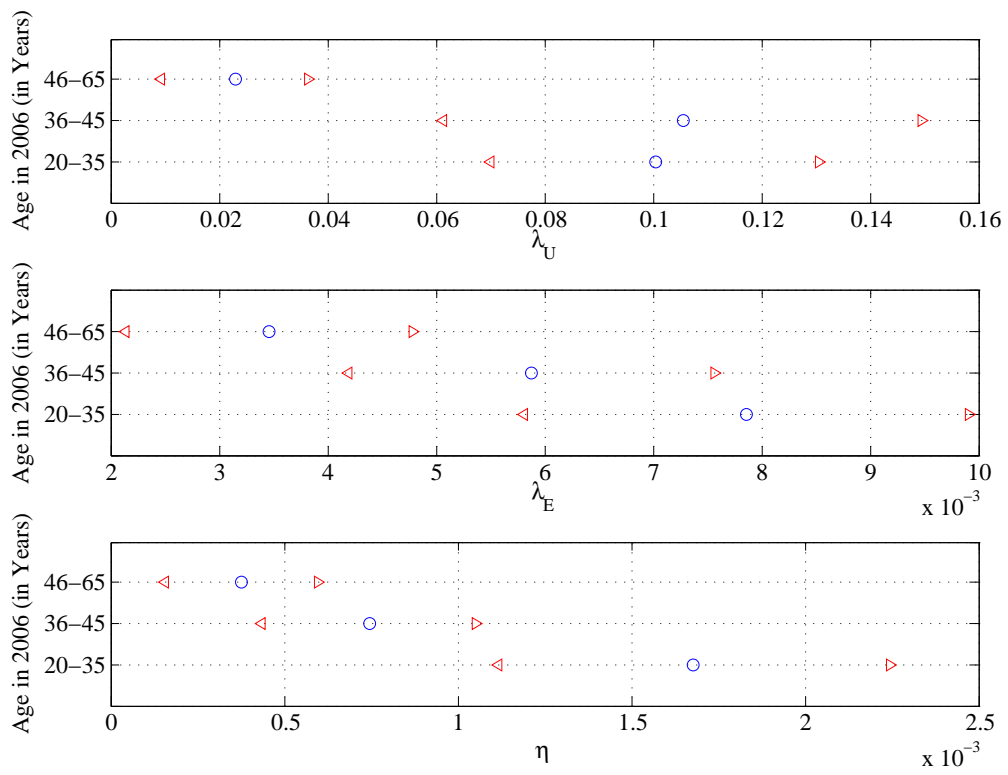
Note: Calculations based on simulations of 2,123 individuals, while changing each parameter at a time and maintaining the remaining parameters in their estimated values. All the equilibrium effects are taken into account in each simulation.

Figure 3.5: Effect of Individual Parameters on Lifetime Inequality Measures - Unskilled Workers



Note: Calculations based on simulations of 7,877 individuals, while changing each parameter at a time and maintaining the remaining parameters in their estimated values. All the equilibrium effects are taken into account in each simulation.

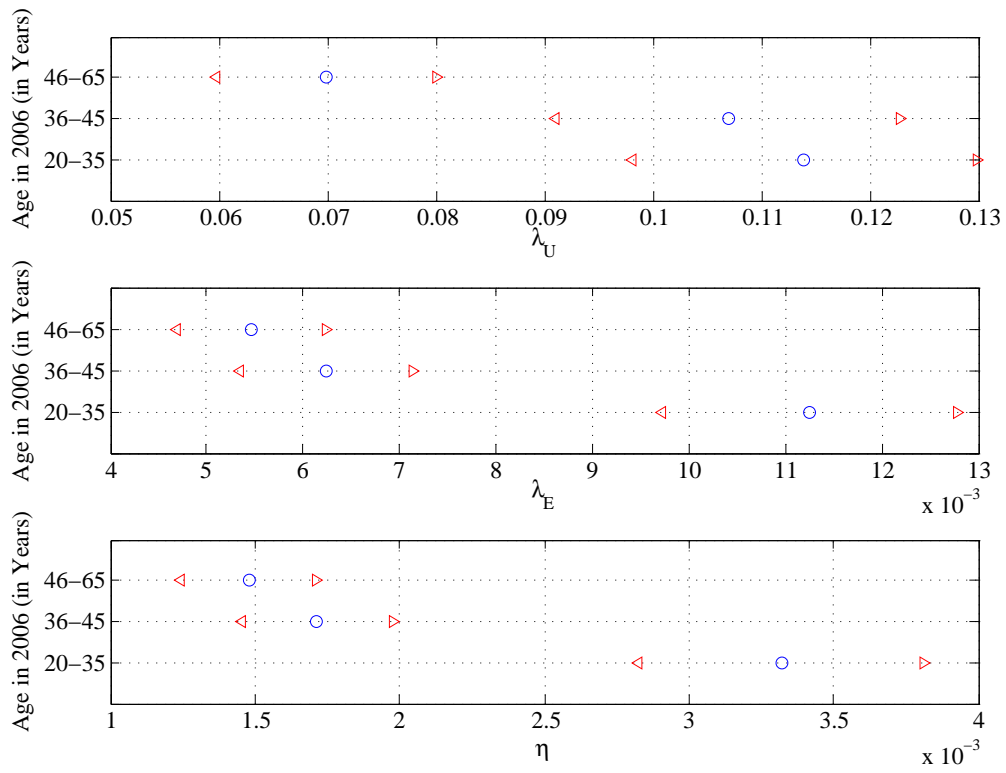
Figure 3.6: Mobility Parameters by Age - Skilled Workers



Note:  $\circ$  represents the estimated parameter and  $\triangleleft$  and  $\triangleright$  a 95 % confidence interval.



Figure 3.7: Mobility Parameters by Age - Unskilled Workers



Note:  $\circ$  represents the estimated parameter and  $\triangleleft$  and  $\triangleright$  a 95 % confidence interval.

## CHAPTER 4

### GENDER GAPS IN EDUCATION AND LABOR MARKET OUTCOMES IN THE U.S.: THE IMPACT OF EMPLOYERS' PREJUDICE (WITH LUCA FLABBI)

#### 4.1 INTRODUCTION

This chapter proposes three contributions. First, it provides descriptive evidence on gender differentials by education in the US labor market over the last twenty years. Second, it uses the structural estimation of a search model of the labor market to identify and quantify the impact of employers' prejudice on labor market gender differentials. Third, it connects both the descriptive and analytical findings to recent policy interventions in the US labor market and performs some policy experiments. For all the analysis, this chapter uses the *Annual Social and Economic Supplement* (ASES or March supplement) of the Current Population Survey (CPS)<sup>1</sup>.

##### 4.1.1 DESCRIPTIVE EVIDENCE

The descriptive evidence is organized following the decision process of an individual deciding to supply labor in the market. First, the outcomes of education decisions are analyzed. Education decisions constitute the most important component of pre-labor market human capital and they influence not only future performance in the labor market but also the decision to participate in the labor market itself. It is also a choice and process where gender asymmetries are present but evolving quickly. Evidence is

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<sup>1</sup>A detailed description of the data and the estimation sample is contained in the Appendix C.1.

provided on the overall quantity of education acquired and on one aspect of the "quality" of education acquired: the field of study. All the evidence on labor market outcomes will be correlated to these previous education decisions. The main result on pre-labor market characteristics is that women acquire more college education than men, reinforcing a trend started with the generation born in 1959. A lot of asymmetry by gender persists in the choice of field of study.

Second, this chapter looks at the decision to supply labor in the market both with respect to the extensive margin (the participation decision) and to the intensive margin (the hours supply decision). This evidence is correlated with education and looks at the evolution over time. Evolution over time is presented by using the full cross-sectional information of each survey year but life-cycle evidence is not presented. This is done in preparation for the second part of the chapter where two labor market equilibria are compared ten years apart (1995 and 2005) and where the equilibrium search model utilized abstracts from life-cycle heterogeneity. The main result from this section is that women supply less labor than men both on the extensive and on the intensive margins. The result shows that part-time usage is a crucial determinant of gender differences in the labor market. Results also indicate that the gender gap is not alleviated by education: the gender gap in the hours worked per week is actually exacerbated by education since it is larger in the College graduates sample than in the overall sample.

Third, this chapter looks at gender earnings differentials in the labor market. Both the raw differential and the differential conditional on standard human capital characteristics are computed. Evidence is also provided on the gender gap at different percentiles of the earnings distribution and on very high-skilled occupations (CEOs and General Managers) to assess the magnitude of the so-called glass-ceiling effect. Results show that women earn about 20% less on average than men. The gap has

been fairly stable in the last 10/15 years, after a period of significant reduction in the 1970s and 1980s. One reason for the persistent gender gap in recent years, in particular among skilled workers, is the large differential at the top of the earnings distribution, a possible indication of glass-ceiling effects.

#### 4.1.2 THE IMPACT OF EMPLOYERS' PREJUDICE

In the second part of the chapter, the source of the observed gender differentials is investigated. Priority is given to gender differentials in the labor market - both in terms of wage differentials and of labor market dynamic - but some inference are also drawn on gender differentials in pre-labor market characteristics by proposing a novel measure of returns to education that takes into account the entire welfare effect of the labor market dynamic. It will be possible to make distributional considerations and to evaluate some determinants of the glass-ceiling but an analysis of labor supply determinants will not be done.

The analysis in the chapter focuses on three main determinants of gender differentials: productivity differences; employers' prejudice; and search frictions. These three determinants constitute a quite exhaustive list of the possible explanations proposed in the literature to account for the observed gender gap<sup>2</sup>. The difficulty, from a quantitative point of view, is to separately identify the contribution of these three components on the observed differential. The methodology used exploits the structure of a specific model - a search-matching-bargaining model with employers taste discrimination - to separately identify and then estimate these three components.

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<sup>2</sup>Two main determinants are left out: gender asymmetries in household production and differential preferences with respect to job amenities. For a review of the first issue see Waldfogel [1998]. The second issue focuses on the relationship between education choices and occupation choices. For an example within the search and matching literature, see Flabbi and Moro [2012].

The model is estimated over two time periods (1995 and 2005); three education levels (Master and PhD; College; and High School); and three samples (full sample, married, married with children). Results suggest that the gender gap in wage offers is smaller than the gender gap in accepted wages on the high education samples but larger on the low education samples. The gender gap in productivity is estimated to be relatively small on the College and High School sample but it is increasing over time. The productivity gap for Master and PhD holders is quite large and increasing over time. The gender gap between workers employed at prejudiced employers and workers employed at unprejudiced employers is larger the higher the education level. The gender gaps in unemployment rates are relatively small in all years and education groups.

In this chapter, the separate identification and estimation of the three main determinants of gender differentials is used to decompose their impact on the gender wage gap. The results show that prejudice has a significant impact in explaining the wage gap but the impact is decreasing over time and it becomes smaller than the impact of productivity on all education groups in 2005. Master and PhD graduates are the exception to the trend: they experience a stronger impact of prejudice in 2005 than in 1995. Thanks to a decomposition of the gender wage gap at different points of the distribution, it is found that the Master and PhD sample shows some evidence of glass-ceiling effects. This evidence is marginally tempered when marital status and the presence of children is taken into account, in particular on 2005.

#### 4.1.3 POLICY EXPERIMENTS AND POLICY IMPLICATIONS

The descriptive section of the chapter shows that gender differentials are by no means limited to average wage differentials, the variable often used in the literature to summarize the "gender gap" in the labor market. Gender differences concerns the shape of

the entire wage distribution, the labor market dynamics across labor market states and the schooling choice preceding the entrance in the labor market. To really judge the overall welfare of labor market participants and to compare welfare across schooling groups and time periods, it is necessary to build an indicator able to take into account all these different elements. Thanks to the estimates of the structural model, it is possible to propose and compute such indicator.

First, the indicator to compute a "welfare return" to schooling is used, i.e. the welfare differentials enjoyed by labor market participants at different levels of schooling. The results show that 1995 female returns were higher than male returns, providing a possible explanation for the higher level of education acquired by women. However, the returns are estimated to be lower in 2005, a result mainly due to the presence of prejudiced employers in the labor market.

Second, policy experiments that mimic the major policy interventions implemented in the US labor market are performed: Equal Pay policies and Affirmative Actions policies. In the equal pay policy, it is imposed that wage schedules cannot be set conditioning on gender. In the affirmative action policy, an employer subsidy to hire women is implemented. The Equal Pay policy is effective in redistributing welfare from men to women but it is never enough to completely close the gender gap. It is more effective for lower education levels than for higher ones and it has larger impacts in 1995 than in 2005. The affirmative action policy has a modest but positive impact on closing the gender gap in welfare. Despite the modest impact, the policy is promising because it is frequently able to close the gap without reducing overall welfare and it targets better the group that is not showing a positive evolution in closing the gap over time: the Master and PhD graduates sample.

## 4.2 DESCRIPTIVE EVIDENCE

### 4.2.1 GENDER DIFFERENTIALS IN PRE-LABOR MARKET CHARACTERISTICS

Figure 4.1 shows the gender gap (women - men) in the percentage of college graduates and Master and PhD graduates. To look at the evolution over-time, the cohort evidence obtained by pooling the survey years data together, limiting the sample to individuals born between 1940 and 1980, is reported.

The most important result is that the gender gap has been shrinking over the last twenty years and it has actually become positive starting with the generation born in 1959 for College and with the generation born in 1971 for Master and PhD. A positive gap means that women acquire more education than men. This is a well-established empirical fact, which is becoming increasingly common among OECD countries [OECD, 2008, Flabbi, 2011]. It is also evidence that has prompted an increasing literature trying to explain why the gap in education is positive while the gender gap in earnings remains negative<sup>3</sup>.

Figure 4.2 shows one dimension of the quality of education: field of study. One possible explanation for the puzzle of a positive education gap together with a negative gender wage gap is that women may choose fields of study correlated with lower wages. While evidence on this correlation may have different sources, Figure 4.2 shows that the asymmetries on fields of study choices are substantial. If the favorite field for both men and women is "Business and Law", almost 20% of men choose "Engineering" while less than 5% of women do. At the same time, almost 15% of women choose "Humanities" compared with less than 8% of men. As a result, many fields see an

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<sup>3</sup>The most complete explanations proposed so far focus on the return to education on the marriage market [Chiappori et al., 2009, Ge, 2011]. For a different explanation based on job amenities, see Flabbi and Moro [2012]. For international comparisons, see Becker et al. [2010].

imbalance in terms of gender distribution: from Figure 4.2, it is possible to observe that the proportion of women in the "Education" and "Medical" fields is much higher than the proportion of women in the population (the red horizontal line). The opposite is true for "Science" and "Engineering". The red horizontal line reports the overall proportion of women in the population giving an immediate picture of the field of study in which there is an over- or an under-representation of women. This gender imbalance in the choice of College major is found on most OECD countries. Most proportions are strikingly similar (the two extremes, "Education" and "Engineering", are almost identical) while a few see a better gender balance in the US sample than in the Italian sample ("Business and Law").

The terminology of Flabbi and Moro [2012] is borrowed to propose just one possible correlation between field of study choice, occupational choice and job characteristics<sup>4</sup>. Figure 4.3 reports the correlation between the occupational choice of women and the degree of "flexibility" in the job by field of study choice. (In this Table flexibility simply means the possibility of working less than 30 hours a week.) The results indicate that the field of study least favored by women ("Engineering") is characterized by the lowest degree of flexibility while the two relative most favored fields ("Education" and "Medical" professions) are characterized by the highest degree of flexibility.

To summarize, the evidence on pre-labor market characteristics shows that women acquire more college education than men, reinforcing a trend started with the generation born in 1959. Women acquire less graduate education than men but the differential is shrinking. Where a lot of asymmetry by gender persists is in the choice of field of study, choice that may be correlated to desirable future job characteristics.

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<sup>4</sup>For some recent country-specific evidence on this correlation in European Countries, see Beffy et al. [2009] and Chevalier [2011].



#### 4.2.2 GENDER DIFFERENTIALS IN LABOR SUPPLY

This chapter analyzes the labor supply evidence by presenting results by education levels. To reduce clutter, only two education levels (College completed or more and less than College completed) are presented. The text will include a discussion on a few statistics for the very highly educated (Master and PhD) and the focus in the following two sections of the chapter will be on three education groups.

Figures 4.4 report evidence on the first labor supply decision: supply labor in the market or not. This extensive margin reports a negative gender gap: men systematically participate in the labor market more than women both on the low education sample and on the high education sample but the differential has been shrinking over time. Education makes a difference: the differential is smaller on the College sample and it has uniformly been smaller over the entire twenty year period under consideration.

Age is also a relevant determinant of participation rates since it is strongly correlated with fertility. The sample has been divided in three age groups roughly describing a period before children (younger than 30); with young children (30-45 years old) and with older children (older than 45). Results show that participation decisions are very sensitive to age but the education differential remains significant. Evidence by cohorts confirms this view because it seems to reflect more life-cycle patterns than major breaks across different generations.

Employment rates are reported in Figure 4.5 following the same structure used in Figure 4.4. Figure 4.5 reports no gender gap in employment rates among college graduates while a small positive gap exists on the low education sample. Notice the big drop in employment rates during the "Great Recession" of the last three years. By computing statistics by age and cohort, it is evident that employment rates are

systematically lower for younger workers and for individuals without a College degree. Interestingly, the lack of a gender gap in employment for the College graduates is a quite old phenomenon, involving cohorts going as far back as 1940.

The labor force dynamic is analyzed by computing Kaplan-Meier estimates of the hazard rate out of unemployment. Only the main results of the exercise are discussed. A first striking result is how much more difficult it is to find a job during the recent recession: 2010 is clearly an outlier when compared with the other years. A second interesting result is that the impact of the recession is pretty homogeneous on all four education/gender groups, in particular a College degree does not seem to cushion the severity of the crisis. Differences among the other years are smaller and the fact that College graduates systematically take more time to find a job suggests that lower hazard rates also reflect "pickier" workers, i.e. workers waiting in unemployment for better job opportunities to come along. Differences between men and women are larger on the College sample than on the overall sample but they do not exhibit a strong trend over time.

This chapter also looks at the intensive margin of the labor supply. Figure 4.6 reports an indicator extremely relevant to assess gender differentials in the labor market: the incidence of part-time work. Results show a very large gender gap: women are more than twice as likely to work part-time as men. The gap is not significantly reduced when focusing on College graduates because the incidence of part-time is smaller for both on men and women with College.

The CPS data also report weekly hours worked but only starting with survey year 1985. As expected, there is a big concentration at 40 hours per weeks: About 50% of the sample declares to work that much. What is interesting is that most of the remaining population of male workers declare to work more than 40 hours per week while most of the remaining population of female workers declare to work less than

that. This gender difference is not alleviated by education, it is actually exacerbated by education because male college graduates are more likely to work more than 40 hours per week than no college graduates. It is also a gender differential that is fairly stable over time.

To summarize, the evidence on labor supply shows that women participate less than men in the labor market but when they do they obtain similar employment rates. The intensive margin of the labor supply shows a large gender gap, mainly due to the much larger incidence of part-time among female workers than among male workers. This gender gap is not alleviated but actually exacerbated by education since it is larger in the college sample than in college graduates.

#### 4.2.3 GENDER DIFFERENTIALS IN THE LABOR MARKET

Figures 4.7 and 4.8 report estimates of the gender earnings gap from 1981 to 2011. The gap is estimated as the coefficient of a dummy variable, that takes the value of 1 if the individual is a woman, in an OLS regression of log hourly earnings. The top panel (Figure 4.7) reports results from a specification including simply a constant and the dummy for woman: it is therefore an estimate of the raw differential at the mean, unconditional on any observables. The bottom panel (Figure 4.8) reports results from a specification including a constant, the dummy for woman, three educational dummies, age linear and squared, two race dummies, a dummy for marital status and a dummy for presence of children younger than 18: it is therefore an estimate of the differential conditional on standard human capital and demographic characteristics. Dotted lines describe the 95% confidence interval.

As it is well documented, the gender gap in wage and earnings is persistent in the US labor market<sup>5</sup>. Figure 4.7 shows a significant convergence for all the 1980s, following a trend that started in the previous decade (not shown). In the following decade, instead, the convergence slows down and then stops completely in the mid-1990s. The trend in the last ten years is less clear, with periods of minor convergence followed by periods of small divergence. The most recent year available (2011) reports the smallest gender earnings gap ever, breaking the 20% mark on the unconditional differential for the first time ever. Figure 4.8 shows a very similar evolution over time but usually at a slighter lower level, implying that human capital differences do not explain the gender gap in earnings (at least under the very simple mincerian specification used).

In Figures 4.7 and 4.8, periods of recession are also reported to show how the gender gap is related to the business cycle, following a literature correlating the cycle, the change in inequality and the gender gap [Lemieux and Fortin, 2000, Biddle and Hamermesh, 2012]. Results show that recent recessions had a very different impact than earlier recessions: in the 1981 and 1990 recessions the gap decreased, while in both the last two recessions the gap increased.

There is a large literature pointing out that the crucial sources of the gender gap in high-income economies may be concentrated at the top of the earnings distribution<sup>6</sup> and at the top of the hierarchical ladder in the firm<sup>7</sup> (the so called glass-ceiling hypothesis). Figure 4.9 looks at the gender gap at different points of the unconditional earnings distribution. Results do not support the presence of a glass ceiling in the

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<sup>5</sup>For over time evidence in the US, see Eckstein and Nagypál [2004]; Blau and Kahn [2006], and Flabbi [2010b].

<sup>6</sup>See Albrecht et al. [2003]; Blau and Kahn [2006] and Bertrand et al. [2010].

<sup>7</sup>See Bertrand and Hallock [2001]; Albanesi and Olivetti [2006]; Bertrand et al. [2010]; and Gayle et al. [2012].

1990s but they are consistent with the presence of a glass ceiling in the last 10/15 years, with a particularly large spike in 2000. Figure 4.10 reports some evidence on the gender asymmetries in the top hierarchical ladder in the firm. Looking at the CPS data used so far, the differentials are large: among CEOs and General Managers, only 20% are women, compared with a presence of women in the labor force which is very close to 50% (Figure 4.10). Overall, the proportion of men in Management Occupations is about 13% compared with about 8% for women. These differentials are essentially constant over-time, even if the time span considered is much smaller than in previous figures because a change in the CPS definition of occupations does not make the values comparable over the entire three decades considered in this study. The data studied by Gayle et al. [2012] looks at the top executives in the Standard and Poor's Execucomp dataset<sup>8</sup>. Thanks to their data, they are able to look deeper in the still relatively large category of "CEOs and General Managers" reported by the CPS. Based on job titles and transitions across occupations, they build seven rankings within the top executives (7th is the lowest and 1st the highest). What is seen in Figure 4.11 confirms the very low presence of women at the top of the firm (no more than 6/7%), with their presence decreasing as the ranking is increasing.

To summarize, the evidence on gender earnings differentials shows that women earn about 20% less on average than men, even when controlling for standard human capital and demographics characteristics. The gap shows a significant reduction from the 35% levels of the early 1980s but has remained fairly stable in the last 10/15 years. One reason for the persistent gender gap in recent years, in particular among skilled workers, is the large differential at the top of the earnings distribution.

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<sup>8</sup>Execucomp contains information on at least the top 5 executives in the S&P 500, S&P MidCap 400, S&P SmallCap 600 firms.

### 4.3 THE IMPACT OF EMPLOYERS' PREJUDICE

#### 4.3.1 THE SEARCH-MATCHING-BARGAINING MODEL

While explicit prejudice has been a part of economic theory for a long time<sup>9</sup>, it is still very difficult to directly observe and measure. One possible way to gauge its presence and impact is to infer explicit prejudice from differential behaviors of labor market agents, conditioning on a parsimonious model of the labor market. A good candidate for such a model is a search-matching-bargaining model.

The model is a good candidate both for theoretical and empirical reasons. From a theoretical point of view, the presence of search frictions justifies the survival of prejudiced employers in equilibrium, as suggested by Heckman [1998] and Altonji and Blank [1999]. From an empirical point of view, search models with matching and bargaining have been used in many empirical applications and have proved to fit the data well [Eckstein and van den Berg, 2007]. Most importantly, Flabbi [2010a] shows that when Becker's taste discrimination is added to the framework, the model is able to separately identify the impact of explicit prejudice, differential productivity and gender-specific search frictions on labor market outcomes.

#### ENVIRONMENT

The model's environment is as follows. The model is developed in continuous time and it is populated by four types of agents who are infinitely lived: two types of workers - Men ( $M$ ) and Women ( $W$ ) - and two types of employers - Prejudiced ( $P$ ) and Unprejudiced ( $N$ ). The employers' type is defined by a difference in preferences: prejudiced employers receive a disutility flow ( $d$ ) from hiring women. Unemployed

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<sup>9</sup>A theory of explicit prejudice ("taste discrimination") was first proposed by Becker in 1957 [see Becker, 1971] and has been very influential on the discrimination literature ever since [see Altonji and Blank, 1999].

workers are looking for jobs and employers with unfilled vacancies are looking for workers to fill them. Search frictions are present in the market so that meetings may take time before they actually happen. There is random matching and there is no on-the-job search. Workers meet employers following a Poisson process with an instantaneous rate of arrival  $\lambda$ . Once an employer and a worker meet, they observe a match-specific productivity value ( $x$ ), which is drawn from an exogenous distribution denoted by the c.d.f.  $G(x)$ . Upon observing the match-specific productivity value and their types, employers and workers engage in Nash-bargaining over the wage. Once a match is formed, it can be terminated following a Poisson process at an instantaneous rate  $\eta$ .

The technology used to produce the homogeneous good produced in the economy is constant returns to scale with labor as the only factor of production. Therefore, the total output at a given employer is the sum of the productivity levels of all his/her matched employees. Workers' utility functions are linear in wages and there is no disutility from working. Employers' utility is linear in profit and in the intensity of discrimination. The intensity of discrimination is defined as the disutility from hiring women that affect prejudiced employers [Becker, 1971]. While a vacancy is unfilled, employers sustain no cost and receive no benefit. While unemployed, workers receive an instantaneous utility (or disutility) flow  $b$  that takes into account search costs, unemployment benefits and other utility benefits and costs correlated with the state of unemployment. Time is discounted by a constant and common rate  $\rho$ . All the model's parameters are common knowledge. Markets are fully segmented along gender-education-year cells. Gender is denoted with  $g$ , employer's type with  $t$ , year with  $y$  and education with  $e$ .

The value of employment for a worker of type  $g$  working at an employer of type  $t$ , producing  $x$ , in year  $y$ , with an education  $e$  is:

$$(\rho + \eta_{gye})V_{gye}[w_{gtye}(x)] = w_{gtye}(x) + \eta_{gye}U_{gye} \quad (4.1)$$

where  $w(x)$  denotes the wage, which is determined by Nash-bargaining. The value of unemployment conditioning on type, education and year is:

$$\begin{aligned} \rho U_{gye} = & b_{gye} + \lambda_{gye} \left\{ (p_{ye} \int \max[V_{gye}[w_{gPye}(x)] - U_{gye}, 0] dG_{gye}(x) \right. \\ & \left. + (1 - p_{ye}) \int \max[V_{gye}[w_{gNye}(x)] - U_{gye}, 0] dG_{gye}(x) \right\} \quad (4.2) \end{aligned}$$

where  $p_{ye}$  is the proportion of prejudiced employer in year  $y$  and in the segmented market with education  $e$ .

## EQUILIBRIUM

Given this environment, workers have a very simple decision to make: accept or reject the match with a given employer. They make this decision by balancing the flow benefit of receiving a wage higher than the current utility of unemployment with the expected benefit of receiving a potentially better offer in the future. Since the present discounted value of being unemployed does not depend on a given wage but only on the entire expected wage offer distribution and the present discounted value of being employed at a given employer is increasing in the wage received, there will exist a wage at which the worker is indifferent between accepting the job or remaining unemployed. This value is called the *reservation wage*. A similar argument holds for the employer. The reservation value is determined as the value at which the agents are indifferent between accepting or rejecting the match.

By adding the optimal decision rules to the value functions, an equation that implicitly defines the only necessary equilibrium object, the value of unemployment



$U$ , is obtained:

$$\begin{aligned} \rho U_{gye} = & b_{gye} + \lambda_{gye} \left\{ p_{ye} \int_{\rho U_{gye} + d\mathbf{I}_{(g=W,t=P)}} [x - d_{ye}\mathbf{I}_{(g=W,t=P)} - \rho U_{gye}] dG_{gye}(x) \right. \\ & \left. + (1 - p_{ye}) \int_{\rho U_{gye}} [x - \rho U_{gye}] dG_{gye}(x) \right\} \end{aligned} \quad (4.3)$$

It is now possible to propose the following:

**Definition 4.3.1** *In each market defined by year and education group, given the vector of parameters  $\{\lambda_{gye}, \eta_{gye}, \rho, b_{gye}, \alpha, d_{ye}, p_{ye}\}$  and the cdf of match-specific productivity values  $G_{gye}(x)$ , the equilibrium is defined by the vectors of values of unemployment  $U_{gye}^*$  that solve equation (4.3), which in turn determine the reservation values characterizing the optimal decision rules.*

The axiomatic Nash-bargaining solution to the bargaining problem faced by workers and employers bargaining over the wage is assumed given the match-specific productivity  $x$  and their types. The solution corresponds to maximizing the product of the worker's and employer's surpluses, weighted by their bargaining power  $\alpha$ :

$$w_{gtye}(x) = \operatorname{argmax}_w \{V_{gye}[w] - U_{gye}\}^\alpha \left\{ \frac{x - d_{ye}\mathbf{I}_{(g=W,t=P)} - w}{\rho + \eta_{gye}} \right\}^{(1-\alpha)} \quad (4.4)$$

The Nash-Bargaining solution has the property that the worker and the employer will always agree to a match when the match is producing a surplus and they agree to share the surplus according to their respective bargaining weight and their outside options. The analytical expressions of the resulting wage schedules makes this concept clear.

First, look at the wage of a man working for a prejudiced or unprejudiced employer (the employer's type has no impact on male workers) with a match-specific productivity equal to  $x$ :

$$w_M(x) = \rho U_M + \alpha(x - \rho U_M) \quad (4.5)$$

The expression states that the wage guarantees the worker his outside option ( $\rho U_M$ ) plus a portion of the surplus ( $x - \rho U_M$ ) equal to the bargaining weight ( $\alpha$ ). The bargaining weight captures factors related to the bargaining strength of workers with respect to employers: the higher the weight, the higher the wage at given productivity. The outside option of the worker is the present discounted value of being unemployed: This value is denoted with  $\rho U_M$  and this expression is formally characterized in equation (4.3). The higher the outside option's utility, the higher the wage at given productivity because the worker will have a better state to go back to if the match is not realized. Finally,  $(x - \rho U_M)$  is the surplus generated by the match because it is the difference between what is produced in the match ( $x$ ) and what is lost if the match is realized ( $\rho U_M$ ). Notice that the employer does not lose anything if the match is realized because the cost of keeping a vacancy open is zero.

Second, look at the wage of a woman working for an unprejudiced employer with a match-specific productivity equal to  $x$ :

$$w_{WN}(x) = \rho U_W + \alpha(x - \rho U_W) \quad (4.6)$$

The expression is exactly equal to equation (4.5) with the difference that the outside option is allowed to be different. The subscript  $M$  is used to denote men and subscript  $W$  to denote women. Notice also that the wage equation has two subscripts:  $W$  to denote women and  $N$  to denote unprejudiced employers. This is necessary because the female wage schedules are employer's type-specific in equilibrium.

Third, look at the wage of a woman working for a prejudiced employer with a match-specific productivity equal to  $x$ :

$$w_{WP}(x) = \rho U_W + \alpha(x - d - \rho U_W) \quad (4.7)$$

The expression is different from (4.6) because the surplus is reduced by the disutility that the prejudiced employers receive when hiring women ( $d$ ). The expression

makes it clear that, as a result of the bargaining process, the cost of prejudice is shared by both the employer and the worker: The higher the discrimination intensity  $d$ , the lower the wage at same productivity.

It is now possible to state the equilibrium decision rules resulting from the model:

1. The optimal decision rules are *reservation values rules* and both workers and employers agree on what these reservation values are. The reservation value rule in this case means that the match will be realized (i.e. both workers and employers agree to enter a job relationship governed by wage equations (4.5)-(4.7)) if the match-specific productivity is higher than the *reservation productivity value*. The wages corresponding to these reservation productivity values are the *reservation wages*.
2. The reservation productivities are different between men and women and they are different between women accepting to work for a prejudiced employer and women accepting to work for an unprejudiced employer. They are denoted with  $x^*$  and defined as follows:

$$x_M^* = \rho U_M \tag{4.8}$$

$$x_{WN}^* = \rho U_W \tag{4.9}$$

$$x_{WP}^* = \rho U_W + d \tag{4.10}$$

3. The reservation wages are worker's type-specific but not employer's type-specific. They are denoted with  $w^*$  and defined as follows:

$$w_M^* = \rho U_M \tag{4.11}$$

$$w_W^* = \rho U_W \tag{4.12}$$

The structure of the equilibrium has some interesting *implications* about the impact of prejudice on labor market outcomes:

1. Everything else equal, the presence of prejudiced employers makes the present discounted value of participating in the market ( $U$ ) lower for women than men [See Proposition 1 in Flabbi, 2010a].
2. Wage discrimination is present at prejudiced employers: Women working at prejudiced employers receive lower wages than men working at prejudiced employers with the *same* level of productivity. This is easy to see by comparing wage equation (4.7) with wage equation (4.5): For a given  $x$ , women earn lower wages because of the negative impact of  $d$  (the direct effect of prejudice) and because the women's outside option is lower than the men's outside option (the equilibrium or "spillover"<sup>10</sup> effect of prejudice).
3. Wage discrimination is also present at unprejudiced employers: Women working at unprejudiced employers are also receiving lower wages for the same productivity. The effect results from comparing equation (4.5) and (4.6): if women's outside option are lower (as stated in the first equilibrium) then unprejudiced employers wage discriminate due to the spillover effects even if they do not have any prejudice against women. This is an interesting result that allows to make a clear distinction between explicit prejudice and wage discrimination.
4. Partial segregation arises in equilibrium, that is women are overrepresented at unprejudiced employers and underrepresented at prejudiced employers. This is an important result to explain, or is at least consistent with the segregation observed in labor market data. It is emphasized that "partial" segregation is obtained as opposed to complete segregation. Complete segregation is a starker result which is at odds with the recent empirical evidence since it implies that prejudiced employers never hire women. This is the setting of the previous, and

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<sup>10</sup>For a formal definition of this spillover effect, see Definition 4 in Flabbi [2010a].

still most influential, model merging search frictions with taste discrimination: Black [1995].

#### 4.3.2 ESTIMATION AND IDENTIFICATION

Search and matching models have been extensively studied and implemented. The identification theory is laid out by Flinn and Heckman [1982]: they show that under an appropriate parametric assumption the crucial structural parameters of the model are identified from data on unemployment durations and accepted wages.

It is necessary to add the identification of the prejudiced parameters to the Flinn and Heckman's result. Flabbi [2010a] shows that, under the same parametric assumptions imposed by Flinn and Heckman [1982]<sup>11</sup>, the proportion of prejudiced employers and the disutility they receive from hiring women are identified. This is a useful result because it allows for the separate identification of the prejudiced parameters, the gender-specific productivity parameters, and the gender-specific search frictions parameters. One parameter that is difficult to identify is the Nash-bargaining weight [Flinn, 2006]. This analysis does not try to identify it and simply imposes a standard assumption in the literature: symmetric Nash bargaining, i.e. workers and employers have the same Nash-bargaining weight which is therefore set to be equal to 1/2.

Estimation is performed by maximum likelihood: after a first stage in which an order statistic (the minimum observed wage) is used to obtain a strongly consistent estimator of the reservation wages  $(w_M^*, w_W^*)$ , the maximization of the resulting concentrated likelihood delivers estimates of all the remaining structural parameters. The likelihood function is provided in Appendix C.2.

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<sup>11</sup>On top of showing that a distributional assumption is essential to obtain identification, they also show that estimation results may be sensitive to the distributional assumption used. In the next subsection, some sensitivity analysis performed in this respect is discussed.

### 4.3.3 RESULTS

#### ESTIMATION RESULTS

The Maximum Likelihood estimates of the structural parameters are reported in Tables 4.2 to 4.4. The model estimation is performed assuming that productivity, for both males and females, follows a log-normal distribution or  $\ln(x) \sim N(\mu, \sigma^2)$ . Under this assumption the average productivity and its variance are:  $\exp(\mu + 0.5\sigma^2)$  and  $(\exp(\sigma^2) - 1)\exp(2\mu + \sigma^2)$ . Therefore,  $\mu$  and  $\sigma$  reported in Tables 4.2 to 4.4 refer to the location and scale parameters of the lognormal gender-specific productivity distribution.  $\lambda$  refers to the exogenous arrival rate of job offers and  $\eta$  to the exogenous termination rate.  $p$  is the proportion of prejudiced employers in the economy while  $k$  is the ratio between the disutility from hiring women suffered by prejudiced employers ( $d$ ) and the expected value of productivity for male. The parameter  $k$  is estimated instead of  $d$  to better scale the comparison across years and samples.

The estimation is performed jointly for 1995 and 2005 but separately by education level. The joint estimation is done to constrain the relative prejudiced preferences to be the same over the 10 years period. Following Flabbi [2010b], it is assumed that the proportion of prejudiced employers is quicker to adjust than preferences, therefore the first one is left free to change over time while the second is constrained to be the same over the two periods. In estimation, the model is reparametrized and the disutility of prejudiced employers relative to the average male productivity is estimated. This ratio is the parameter  $k$  reported in Tables 4.2 to 4.4.

The estimates of the structural parameters are in line with previous literature [Flabbi, 2010a,b, Flinn, 2006, Bowlus and Eckstein, 2002]: women usually have higher arrival rates of offers and lower average productivity. The proportion of prejudiced employers and the relative disutility of discrimination are consistent with the result

of Flabbi [2010b]: the labor market for College graduates sees a decrease in the proportion of prejudiced employers and a disutility value equal to about 30% of average male productivity. If High School also experience a decrease in the proportion of prejudiced employers, this is not the case on the sample of Master and PhD. However, the estimates of the prejudiced parameters are much more imprecise on this sample, probably due to the smaller sample size.

Table 4.5 and 4.6 shows some relevant predicted values obtained from the estimation results. Table 4.5 focuses on the cross-sectional distribution of productivity and wages. The Accepted Wages distribution corresponds to the observed wage data and it is the measure conventionally used to compute the gender wage gap. The wage offer distribution is not directly observed and it is possible to predict it thanks to the model structure: It indicates the wage offers actually received by men and women before they decide whether to accept them or not. In many respects, the wage offers distribution represents a better measure to gauge the actual disadvantage or wage gap experienced by women because it avoids the selection bias due to gender differences in reservation wages<sup>12</sup>. The productivity distribution is also unobserved and it is the true primitive distribution in the model. Finally, another unobserved component that can be recovered thanks to the structural estimates is the assignment of women to prejudiced and unprejudiced employers.

The gender gap in accepted wages is in line with the descriptive evidence, ranging from 26% to 20% overall. The gap is decreasing in the High School sample, stable in the College sample and actually increasing in the Master and PhD sample. The evidence of the gender wage gap over time - for example Eckstein and Nagypál [2004], Blau and Kahn [2006] and Flabbi [2010b] - report a stable or decreasing gap but they

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<sup>12</sup>This is one of the advantage of obtaining structural parameters estimates. The first paper estimating a search-matching-bargaining model, Eckstein and Wolpin [1995], makes a similar argument in the context of returns to schooling estimation.

do not focus on schooling level as high as Master and PhD. This relative disadvantage of very high skilled women is a robust finding throughout the chapter.

The gender gap in wage offers is smaller than the gender gap in accepted wages at high education levels and larger at low education levels. This is evidence consistent with high skilled women being relatively more choosy than similarly educated men. Two possible sources of this behavior are: 1) gender and education-specific preferences for job amenities and 2) gender asymmetries in household-level decisions. An example of the first is the result in Flabbi and Moro [2012]: women with a College degree value the job amenity "work flexibility" more than women with an High School degree. An example of the second is the result in Flabbi and Mabli [2010]: once the fact that labor market decisions are made at the household level are taken into account, gender differentials in wage offers are estimated to be smaller than in an individual search model. Both elements are ignored in the version of the model estimated. However, in line with the second approach, the model is also estimated conditioning on two crucial elements related to household behavior: marital status and the presence of young children in the household. The results will be commented starting from the earnings decomposition in Table 4.8.

The gender gap in productivity is relatively small in the College and High School sample but it is increasing over time. The productivity gap for Master and PhD holders is quite large and increasing over time. As a result, and as will be seen in the next section, the differential in productivity are responsible for most of the gap observed in the highest education group. However, since important factors such as preferences for job amenities and gender asymmetries in household-level decisions are ignored, this result should be regarded with caution. Productivity is introduced in the model in a very reduced form way and it may well be the residual component that absorbs dynamics not explicitly modeled in the framework.



The gender gap between workers employed at prejudiced employers and workers employed at unprejudiced employers is larger the higher the education level. For example, the gender gap in wage offers at prejudiced employers in the Master and PhD sample in 2005 is equal to 55% while at unprejudiced employers it is equal to 80%. This 25 percentage points difference decreases to about 2 percentage points on lower education levels. This result shows that even if the overall impact of prejudice on the high skilled sample is smaller than the impact of gender-specific productivity, it still has major impact in generating wage discrimination.

Table 4.6 shows some evidence on labor market dynamics: the hazard rates out of a given labor market state and the proportion of workers in each labor market state in equilibrium. The overall hazard rate out of unemployment is higher for women, a result explained both by higher arrival rates of offers and by lower reservation wages (see Table 4.2). The gender gaps in unemployment rates are relatively small. Larger but not big differences are observed in the distribution of men and women between prejudiced and unprejudiced employers. Notice that the overall employment by employer type is reported so when the proportion of prejudiced employers is extremely high (as in High School sample in 1995) most of employed workers must work for them. This only partial segregation result implies that policies imposing quotas by employers (as common in some Affirmative Action policies, see Section 4.3) would not be very effective in reducing wage discrimination and in alleviating the impact of prejudice on labor market outcomes.

The results are potentially sensitive to the distributional assumptions. In order to analyze how sensitive the estimation results are to assuming a lognormal, the model was estimated using two additional distributions. In the first exercise, it is assumed that productivity follows a gamma distribution, that is  $x \sim \Gamma(\alpha, \theta)$  where  $\alpha$  and  $\theta$  are the shape and scale parameters and the average productivity and its variance

are defined as  $\alpha\theta$  and  $\alpha\theta^2$ , respectively. In the second exercise, it is assumed that productivity follows a normal distribution, that is  $x \sim N(\mu_x, \sigma_x^2)$ , where  $\mu_x$  and  $\sigma_x^2$  are directly the average productivity and its variance. It is important to mention that these three distributions satisfy the recoverability condition, which is crucial under the identification strategy of Flinn and Heckman [1982]. The starting values used in the likelihood maximization procedure were the same for all the estimation exercises. The equivalence between the distributional parameters was found using the definitions for the average productivity and its variance.

The results of this sensitivity analysis indicate that some estimated parameters are indeed sensitive to the distributional assumptions. Comparing the estimates under the gamma distribution assumption with the benchmark estimates obtained using a log-normal distribution, large differences are not found in the mobility parameters (for example the largest difference in job arrival rates is just 0.04) but there are large differences in the prejudice parameters (the largest differences for  $p$  and  $k$  are, respectively, 0.7 and 1.4). Comparing the estimates under the normal distribution assumption with the benchmark, larger differences are found in the prejudiced parameters and there are convergence problems on some samples.

#### GENDER WAGE GAP DECOMPOSITION

Table 4.7 reports a decomposition of the gender wage gap at different points of the accepted wage distribution. The gap is decomposed into the three sources of gender differentials assumed in the model: productivity, search frictions and prejudice. The decomposition is performed by taking into account equilibrium effects, i.e. by taking into account that changing the labor market environment induces individual agents to adjust their behavior.

The following procedure is implemented. To isolate the impact of productivity, it is imposed that all the other differences between men and women do not exist. In particular, it is assumed that there are not prejudiced employers in the economy and that men and women face the same search frictions. Given this new environment, the new optimal decision rules are computed and new accepted wages distributions are obtained. On this counterfactual accepted wages distributions, average accepted wages for men and women are computed and the ratio of women values over men values are taken. These ratios are reported in the Table 4.7. For example, the first row of College graduates in Table 4.7 states that if the only difference between men and women was the estimated differential productivity, then the observed wage differential at the mean of the entire distribution would be much smaller than that observed in the data: 8.9% as opposed to 22.1%. To isolate the impact of prejudice, the same procedure is followed: productivity and search frictions of women are fixed to those of men but the proportion of prejudiced employers and their disutility are made to be equal to the estimated value. The equilibrium is recomputed and the statistics on the counterfactual wage distribution are obtained. The same exercise is done to isolate the impact of search frictions: the only parameters allowed to be different are the arrival rate of offers and the job termination rate. The "all parameters" exercise is a sort of goodness of fit: wage offers distributions are generated from an environment with all the parameters set equal to the point estimates.

Differences in productivity are the most important factor in explaining the wage gap for the top education level in 1995: Productivity differentials alone will generate the entire differential observed at the mean. This strong impact becomes smaller in 2005 and it is significantly smaller on the College sample but similar on the High School sample. The impact of search frictions always plays in favor of women: a reverse gender wage gap would actually be observed if the only differences between

men and women in the labor market were due to search frictions<sup>13</sup>. Finally, the impact of prejudiced employers is very strong for College graduates in 1995: Prejudice is the most important factors in explaining the wage gap for this year and education group. The impact of prejudice becomes smaller over time, becoming less important than the impact of productivity in 2005. Instead, the top education group (Master and PhD) shows the opposite trend: smaller impact in 1995 and stronger impact in 2005.

The top education group also shows a different behavior in terms of wage gap at top percentiles. This evidence is important to link back to the glass-ceiling issue mentioned in the descriptive section. Master and PhD graduates in 2005 are the only group exhibiting evidence of glass-ceiling, that is a wage gap increasing as one moves toward the top of the accepted wage distribution. This increasing wage gap is captured by the model but with a much smaller magnitude than in the data.

Table 4.8 reports the wage gap decomposition conditioning on marital status and the presence of children. Comparing the overall sample with the sample of married individuals and the sample with married individuals with children, the decomposition changes but the magnitudes are similar. The most striking result is on the sample of Masters and PhDs in 2005: in the sample of married with kids, productivity becomes less important while prejudice becomes more important in explaining the wage gap. This result is present but less strong in 1995 and it is not present on the other education groups.

The overall conclusion on the decomposition analysis is that most of the results confirm Flabbi [2010b]: Prejudice has a significant impact in explaining the wage gap but the impact is decreasing over time, reaching a level smaller than the impact of differential productivity on all education groups in 2005. The disturbing exception

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<sup>13</sup>The positive impact of search frictions is mainly driven by the higher arrival rate of job offers to women (see Table 4.2).

to the trend, missed by Flabbi [2010b] since he considers only College graduates, is the top education group: Master and PhD graduates experience a stronger impact of prejudice in 2005 than 1995. By estimating the model conditioning on individuals married and with children, it is observed that a good portion of this impact is driven by this specific sample. This result would imply that the impact of prejudice is one of the possible channels of the impact of fertility decisions on labor market outcomes. Master and PhD graduates is also the education group showing evidence of glass-ceiling in 2005, confirming the view that sees the glass-ceiling as the remaining obstacle to reach gender equality in the labor market. However, the model does not have strong prediction in terms of the sources of the glass ceiling because it is only able to qualitatively match the gap at different percentiles of the distributions and it is unable to provide a precise quantitative fit<sup>14</sup>.

#### 4.4 POLICY IMPLICATIONS AND POLICY EXPERIMENTS

It has long been recognized that the presence of discrimination and prejudiced behavior generates inefficiencies and negative externalities<sup>15</sup>, therefore presenting an opportunity for policy interventions. The United States has a relatively long tradition of anti-discriminatory laws targeting the labor market. They can be broadly separated between Equal Employment Opportunity policies and Affirmative Action policies, even if the difference between the two types of policies tends to be starker in theory than in practice [Holzer and Neumark, 2006]. The results of the Descriptive Section of the chapter confirm systematic differences in labor market outcomes for

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<sup>14</sup>One possible reason for this poor fit is the imprecise estimates of the prejudiced parameters. Probably due to the small sample size, the estimate of the disutility suffered by the prejudiced employers hiring Masters and PhDs is very imprecise. See Table 4.2. parameter  $k$ .

<sup>15</sup>An example of negative externality generated by the formal model presented in this chapter is the spillover-effect inducing unprejudiced employers to wage discriminate.

men and women. The results of the more quantitative section of the chapter suggest the presence of explicit prejudice against women and of a significant amount of wage discrimination and segregation. The main policy implication is therefore that policy interventions could be justified. More specific policy implications can be drawn by simulating policy interventions exploiting the estimates of the labor market environment generated in Section 3. This is the objective of this last section of the chapter. Before articulating specific policies, though, it is necessary to define the welfare measure to be used to evaluate them. In doing so, it is also important to say something about pre-labor market decisions, which - as shown in the descriptive section of the model - are also significantly influenced by gender.

#### 4.4.1 WELFARE MEASURE AND RETURNS TO SCHOOLING

The overall welfare of labor market participants depend on their current labor market state and, if employed, on their current wage. However, it also depends on the labor market dynamics related to the transitions between labor market states, the movements over the wage distributions and the durations in each state. A summary measure of overall workers' welfare should then go beyond the comparison of wage gaps presented in Section 4.2.3.

One relative straightforward way to proceed is assigning to each labor market state occupied by workers in steady state the corresponding utility value (i.e. the wage if the worker is employed and the flow utility of unemployment if the worker is unemployed) and then averaging out these utilities values according to the equilibrium steady state distribution. This summary measures take into account both the cross-sectional and the dynamics components of the labor market: the first is captured by the utility values associated to the labor market states and the second by

the distribution over them since the distribution is directly related to durations and transitions probabilities<sup>16</sup>

This welfare measure is first exploited to address some determinants of education decisions. It has been seen that women acquire more education than men even if the usual returns to schooling do not seem to suggest higher returns for women than men in the labor market. This chapter can contribute to the debate by computing the returns based on the welfare measure presented. It is also possible to perform the counterfactual experiments of computing what the returns would be if there were no prejudiced employers in the labor market. The results are reported in Table 4.9 where the gender-specific return of each schooling level is computed for each year. The first column states that completing Master or PhD increases welfare on average by about 26.8% with respect to simply completing College. The returns increase to 92.5 with respect to completing only High School and they are about 51.8% when comparing College with High School.

The comparison of men and women leads to one of the most interesting results of this analysis. In 1995, female returns are higher than male returns. This result may provide an explanation for the empirical puzzle found in the descriptive section where women with higher education levels but lower hourly wages than men are observed. By simply looking at cross-sectional wages, it is being ignored that women may have more to gain in terms of the overall labor market dynamic by acquiring additional education. Women completing Masters and PhDs receive a 30.7% return with respect to College and a 100.7% return with respect to High School; men receive, respectively, a 21.5% return and a 82.4% return. However, in 2005 there is essentially no difference in the returns between men and women, implying that the incentives

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<sup>16</sup>An in depth discussion of this and similar welfare measures is in Flinn [2002b]. For the analytical expression of the welfare measure used here, see Flabbi [2010a], Appendix A.5, Definition 5.

that have in the past induced women to acquire more education may be coming to an end. The counterfactual exercise in which the same measures are computed eliminating prejudiced employers (and taking into account equilibrium effects) implies the following results: If prejudice were to be eliminated in a market similar to the one estimated in 2005, then the welfare returns to MA and PhD would be back to be higher for women than men. Both results are robust to estimating the model only on the sample of married individuals with children younger than 18 years old, as shown in the bottom panel of Table 4.9.

#### 4.4.2 EQUAL EMPLOYMENT OPPORTUNITY POLICIES

*Equal Employment Opportunity* policy interventions date back at least to the *Civil Rights Act* of 1964 which made it unlawful for an employer to "fail or refuse to hire or to discharge any individual, or otherwise to discriminate against any individual with respect to his compensation, terms, conditions or privileges or employment, because of such individual's race, color, religion, sex, or national origin." [Section 703 (a)] The Act also established a specific institutional body to implement the law: *The Equal Employment Opportunity Commission* (EEOC). The role of the EEOC has been progressively expanded by subsequent legislation and the Commission is now responsible to enforce all the federal statutes prohibiting discrimination.

*Equal Pay* policies - i.e. policy specifically aiming at eliminating pay discrimination - are an active part of the equal employment opportunity policy agenda. The first Act signed by President Obama into Law after his inauguration is an example of equal pay policy. *The Lilly Ledbetter Fair Pay Act* of 2009 is a federal statute amending the *Civil Rights Act* of 1964 and stating that the 180-day statute of limitation for filing an equal-pay lawsuit regarding pay discrimination resets with each new discriminatory paycheck. Another related policy initiative is the *Paycheck Fairness Act*, which



updates and strengthens the *Equal Pay Act* of 1963 to ensure better protection against sex-based pay discrimination. The Act has the objective of preventing retaliation against workers who voluntarily discuss or disclose their wages and it allows women to receive the same protections for sex-based pay discrimination that are currently available to those subject to race or ethnicity-based discrimination<sup>17</sup>. In the context of an economic model, an equal pay policy can be defined as any policy that imposes restrictions on the wage determination with the objective of equalizing differentials among clearly identified groups. A simple implementation of such a policy within the Search-Matching-Bargaining model of the previous section would be to require each employer to pay the same wage to workers with identical productivity. Enforcement of such a policy can be guaranteed by assuming that the public authority responsible of enforcing (say, the EEOC) has the possibility of observing the match-specific value of productivity. Clearly, this is a very strong assumption since the measures used to proxy productivity are often quite limited. An alternative way to think this equal pay policy is requiring that gender cannot be observed when wages and hiring are decided. Very limited examples of such a policy have been implemented in practice. Blind auditions to hire musicians implemented by some of the major US orchestras are probably the most well known [Rouse and Goldin, 2000].

The requirement that each employer has to pay the same wage to workers with identical productivity is imposed by interpreting the Nash bargaining wage schedules defined in equations (4.5)-(4.7) as reduced form sharing rules. As a result, offered wages are the average between the wages that would have been offered without the policy, where the average is over the respective proportions of men ( $m$ ) and women

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<sup>17</sup>The *Paycheck Fairness Act* was recently reintroduced in the 112th Congress after having twice passed the U.S. House of Representatives but falling two votes short of a Senate vote on its merits in the 111th Congress.

in the population. The new wage equations are:

$$w_N(x) = \rho U + \alpha[x - \rho U] \quad (4.13)$$

$$w_P(x) = \rho U + \alpha[x - (1 - m)d + \rho U] \quad (4.14)$$

where:

$$\rho U = m\rho U_M + (1 - m)\rho U_W \quad (4.15)$$

Notice that by definition the wage equations are not gender-specific. However, they remain employer-specific, as indicated by the subscript  $P$  and  $N$ .

Results of the policy are summarized in Table 4.10. For each year, the first column of Table 4.10 reports the Benchmark model, the second the Equal Pay policy experiment and the third the Affirmative Action policy experiment that will be discussed in the next section. The Benchmark model is the model simulated using the point estimates obtained by the estimation procedure. The table reports the average welfare values by gender, year and education normalized with respect to the men's average welfare value of the appropriate year-education cell. The top panel reports values obtained from the entire sample estimates; the bottom panel reports values obtained from the married with children sample estimates. For example, looking at the first column in 2005 it is observed that the average welfare of MA and PhD women is 76% of the average welfare of MA and PhD men. The value increases as education decreases, reaching about 80% on the High School graduates sample.

The Equal Pay experiment is effective in redistributing welfare from men to women but it is never enough to completely close the gender gap. In general, the equal pay policy is more effective in reducing the gap at low education levels than at high education levels. Due to the equilibrium effects and the presence of spillover, the policy has the potential to generate average net gains, i.e. a situation where the average benefit received by women is higher than the average loss experienced by

men. By looking at the Overall average welfare value, it is observed that this is the case only for MAs and PhDs in the married with children sample. It is also marginally true on the entire sample for College and High School graduates in 1995. In conclusion, the policy imposes a very strong requirement in terms of wage determination but it does not seem to generate very large effects, with the possible exception of very high skilled individuals who are married and have young children. On the overall sample, it is a policy more effective for lower education levels than for higher ones and it has larger impacts in 1995 than in 2005.

#### 4.4.3 AFFIRMATIVE ACTION POLICIES

*Affirmative Action* policies in the labor market officially starts in the US with the 1961 *Kennedy Executive Order #10925* that mandates "affirmative action" to avoid discrimination by race in the labor market. The 1967 *Johnson Executive Order #11375* extends its application to cover women. In the legislative and policy debate an Affirmative Action policy is any anti-discrimination policy that requires proactive steps [Neumark and Holzer, 2000]. In the economic literature, an Affirmative Action policy is frequently described as a "quota" policy, i.e. a system of exogenously imposed numerical yardsticks for minority in hiring, federal contracting or school enrollments. A quota system definition was not mentioned in the original Presidential Executive orders but, given its convenience in providing objective measures and targets, was introduced in the subsequent regulations governing the executive orders. For example, the 1968 Department of Labor Regulations governing the 1967 Johnson executive order requires explicitly to identify "underutilization" of women and minority. The quota system definition is also the definition most frequently enforced by the Equal Employment Opportunity Commission (EEOC).

The difference between "proactive steps" and "exogenously imposed quota" seems to inform a lot of the debate on affirmative action in the labor market and in education. Neumark and Holzer [2000] provide an extensive review of the economic and public policy literature and conclude that the difference is crucial both in terms of effectiveness and in terms of political viability of the policies. Their overall conclusion is that affirmative action in the US has offered "significant redistribution toward women and minorities, with relatively small efficiency consequences." Donohue and Heckman [1991] focus on the impact of the Civil Rights legislations on labor market outcomes of African-Americans. They also broaden the definition of affirmative action beyond a simple quota system and conclude that the policies had a significant role in improving labor market outcomes. The two most recent Supreme Court opinions about affirmative action - *Grutter v. Bollinger* and *Gratz v. Bollinger* - were delivered on June 24, 2003 and stress the unconstitutionality of explicit quota policies but the admissibility of proactive policies. Discussing, respectively, the admission policy to the College and Law School of the University of Michigan, Justice O'Connor states in the majority opinion that "a race-conscious admission program cannot use a quota system" but a "narrowly tailored plan system" in which "race or ethnicity" may be considered "a 'plus' in a particular applicant's file" constitutes a legitimate affirmative action policy. In conclusion, the tendency of the legislation and the public policy debate has been to push affirmative action policies away from rigid and exogenous quota target toward other proactive steps that could endogenously generate similar outcomes.

In line with this debate, this chapter proposes an affirmative action policy which is not a quota policy but a proactive step in the form of a subsidy. The policy is defined as a flow subsidy received by an employer for each woman hired. The subsidy is paid as a lump-sum tax on workers. Defining with  $\gamma$  the subsidy and with  $t$  the

endogenous tax rate necessary to finance it, the new wage equations become:

$$w_M(x, \gamma) = \rho U_M(\gamma) + t(\gamma) + \alpha[x - t(\gamma) - \rho U_M(\gamma)] \quad (4.16)$$

$$w_{WN}(x, \gamma) = \rho U_W(\gamma) + t(\gamma) + \alpha[x + \gamma - t(\gamma) - \rho U_W(\gamma)] \quad (4.17)$$

$$w_{WP}(x, \gamma) = \rho U_W(\gamma) + t(\gamma) + \alpha[x + \gamma - d - t(\gamma) - \rho U_W(\gamma)] \quad (4.18)$$

The first equation states that men receive a wage that should compensate for the tax they pay but takes into account the reduced surplus implied by the tax. The second equation states that women working at unprejudiced employers receive the same tax effects but at the same time see the surplus increased by the subsidy  $\gamma$ . Finally, the third equation states that women working at prejudiced employers receive similar impacts from the presence of the tax and the subsidy but still share the cost of the disutility implied by prejudice. The tax rate and the value of unemployment are denoted as a function of  $\gamma$  to emphasize that they are endogenous objects changing with the subsidy.

A subsidy does not impose any predetermined quota but by being offered only for hiring women, definitely makes gender "a plus in" some "applicant's file", as stated in the Supreme Court opinion. The impact of the policy is magnified by the spillover effects: not only does the presence of a flow subsidy have a direct positive impact on women wages because firms receive additional revenue from hiring them but it also has an indirect positive impact because it increases women's outside option. The subsidy is fixed at 5% of men's average wage in the corresponding year and education group.

The results of the subsidy policy are reported in the third column of each year in Table 4.10. The policy is less effective in closing the gap than the equal pay policy is but at the same time it is generating more net gains. Net gains are realized in both 1995 and 2005 on the College sample and in 1995 on the Master and PhD

sample. Another advantage of the policy is that it can be calibrated more precisely by increasing or decreasing the subsidy and its costs can be distributed in a variety of ways by changing the structure of the tax necessary to support it. In this respect, the lump-sum tax implemented here is the least distortionary for the economy but it is also the most costly for men. If even under this scheme, more than half of the education-year combinations generate positive gains then an affirmative action policy structured as a subsidy should be seen as the policy with the larger potential for success among the two policies considered here. It is also the policy that generates the largest impact on the group that the previous evidence has shown to be the most problematic: Women with top education skills, supplying labor in the most recent years.

In conclusion, an affirmative action policy structured as a relative modest subsidy provided to employers that hire women has a modest but positive impact in closing the gender gap in welfare. Despite the modest impact, the policy is promising because it is frequently able to close the gap without reducing overall welfare and it is effective in targeting the most problematic education and demographic group: Master and PhD graduates who are married and with young children, observed in 2005.

## 4.5 SUMMARY AND CONCLUSIONS

### 4.5.1 SUMMARY OF RESULTS

Three main results emerge from the descriptive evidence on gender differentials by education in the US labor market over the last twenty years.

1. Women acquire more college education than men, reinforcing a trend started with the generation born in 1959. The proportion of women with a Master or

PhD degree is still smaller than the proportion of men but the differential is shrinking.

2. Women participate less than men in the labor market but when they do, they obtain similar employment rates. The intensive margin of the labor supply shows a large gender gap, mainly as a result of the larger incidence of part-time work among female workers. The gender gap in labor supply is not reduced but actually magnified by additional education.
3. The gender earnings gap is about 20%, even after controlling for standard human capital and demographic characteristics. The gap shows a significant reduction over time (it was about 35% in the early 1980s) but has remained fairly stable in the last 10/15 years. One reason for the persistent gender gap in recent years among highly-educated workers is the large differential at the top of the earnings distribution, an evidence often correlated with "glass-ceiling" effects.

A search-matching-bargaining model is used to investigate some of the sources of the observed gender differentials. The chapter focuses on gender differentials with the objective of isolating the impact of three determinants of gender gaps: productivity differences; employers' prejudice; and search frictions. Four main results emerge from the analysis.

1. Prejudice has a significant impact in explaining the wage gap but the impact is decreasing over time and it becomes smaller than the impact of productivity on all education groups in 2005.
2. Search frictions actually favor women, thanks to the higher frequency with which they receive job offers.

3. Master and PhD graduates are an exception to the decreasing impact of prejudice over time: they experience a stronger impact of prejudice in explaining the wage gap in 2005 than in 1995. Results show that a good portion of this result is due to the sample of individuals married and with young children.
4. The impact of the three sources of the gender wage gap are also decomposed at different point of the distribution: the data shows evidence of glass-ceiling effects on the Master and PhD sample in 2005, a result that only the equilibrium effects of all three factors together is able to partially explain.

The structural estimates of the model are used to build a welfare measure to evaluate returns to education and two policy interventions. The first policy is an equal pay policy imposing one wage at same productivity, the second is an affirmative action policy providing incentives to hire women. Three main results emerge from the exercise:

1. In 1995, female returns to schooling estimated using the welfare measure are higher than male returns. This new result provides a rationale for the apparent empirical puzzle of women acquiring more education than men even if they are paid less for these skills in the labor market. In 2005, female returns are estimated to be lower than male returns, implying that women attitudes toward education could change, reversing the positive education gap.
2. The equal pay policy redistributes welfare from men to women but it is not able to fully close the gender gap. Given the strong requirement in terms of wage determination imposed by the policy, it is believed that it is not very effective.
3. The Affirmative Action policy has a smaller impact on closing the gender gap than the equal pay policy but it is more likely to generate net welfare gains.



The impact of the policy is increasing in the education level of the worker and it seems to target well the most problematic education and demographic group: Master and PhD graduates who are married and with young children, observed in 2005.

#### 4.5.2 SHORTCOMINGS OF THE MODEL

As any policy evaluations using the structure and the estimated parameters of a highly stylized model, the results depend on the assumptions made in this analysis. A few of these simplifying assumptions are discussed, choosing the more relevant ones for the policy implications obtained. First, it has been assumed that workers do not search for new jobs while they are employed. Removing this assumption may give additional opportunities to women to leave prejudiced employers and potentially reduce the impact of discrimination on labor market outcomes. If this is actually the case, then it crucially depends on the gender differential in the arrival rate of offers while working. Since a lot of the time use evidence shows strong gender asymmetries in the time devoted to household production, it is not clear if women will have enough time to search on the job. If they do not, then the results of an on-the-job search model should not be radically different from the results found with the model.

Second, it has been assumed that the proportion of prejudiced employers is fixed and exogenous, even if their impact on labor market outcomes are allowed to be endogenous. If it was possible to let the proportion of prejudiced employers depend on the model parameters, then it would be possible to study the impact of the policy experiments on prejudiced employers who actually survive in equilibrium. For example, the affirmative action policy, by giving incentives to hire women, is clearly favoring employers with lower costs in doing so, that is employers that do not receive

any disutility from hiring women. In this respect, the policy experiments of Section 4 should be considered a lower bound of the possible impact of the policies considered.

Finally, it has been assumed that a job is fully described by its wage, with no other job characteristics taken into consideration. This is a crucial limitation when comparing men and women since they have different preferences over job characteristics. For example, Flabbi and Moro [2012] claim that job flexibility may be crucial in explaining not only gender differentials in the labor market but also gender differentials in education. As a result, technology and legislation able to reduce the cost of part-time or tele-commuting may accommodate preferences for flexibility, increase the range of jobs available to women, and possibly decrease opportunities for prejudiced employers.

#### 4.5.3 CONCLUSIONS

It is believed that the evidence provided in this chapter indicates that gender gaps in labor market outcomes are far from being settled issues. On top of the traditional issues of lower participation rates and gender gaps in wages, new issues that are likely to become more relevant in the future include:

1. Convergence in education levels is not enough to close gender gaps in the labor market.
2. Evidence of "glass-ceiling" effects. The evidence includes a marked underrepresentation of women in top positions at the firm and a larger gender wage gap at the top of the wage distribution.

The conclusion of the analytical contribution is that prejudice may still have a role in explaining the evidence. Even if the magnitudes of the effects are conditional on a highly stylized model, at least one scenario where the possibility of the presence

of prejudiced employers in the labor market has substantial effects is characterized in some details. In particular, it is responsible for the reversal of the return to schooling ranking in recent years and it may explain up to 44% of the gender wage gap of the top education group (Master and PhD) in 2005.

If prejudice is still important, then policy interventions may be effective in attaining both efficiency and welfare gains. The model in this chapter is used to evaluate an equal pay policy and an affirmative action policy. Among the policies considered, an affirmative action policy structured as a relative modest subsidy provided to employers for hiring women is favored. This policy is favored because it is frequently able to close the gender gap without reducing overall welfare and because it is effective in targeting the group that should take center stage in the future debate about gender differentials: high-skilled, high-earners workers, who also have family responsibilities.

Table 4.1: Descriptive Statistics - Estimation Sample

		Master and PhD		College		High School	
		1995	2005	1995	2005	1995	2005
Observations							
N		711	861	2290	2891	3942	4019
N (Wages,Women)		306	437	1071	1420	1856	1850
N (Duration,Women)		5	9	45	54	92	106
N (Wages,Men)		394	403	1141	1362	1867	1933
N (Duration,Men)		6	12	33	55	127	130
Hourly Earnings in Dollars							
Overall							
	Average	27.79	31.26	22.86	24.74	15.60	16.46
	Std. Dev.	12.89	36.74	11.73	15.44	7.35	8.22
Women							
	Average	24.55	26.43	19.79	21.83	12.88	14.20
	Std. Dev.	10.10	12.04	10.19	15.97	5.92	7.11
Men							
	Average	30.30	36.49	25.74	27.78	18.30	18.63
	Std. Dev.	14.20	51.06	12.34	14.24	7.63	8.62
Diff(%)							
	Average	-18.97	-27.56	-23.11	-21.41	-29.64	-23.81
Monthly Unemployment Duration							
Overall							
	Average	6.73	3.87	4.38	5.06	4.12	4.36
	Std. Dev.	7.07	4.19	5.15	5.79	5.12	5.15
Women							
	Average	4.02	4.18	3.82	4.42	3.69	4.20
	Std. Dev.	4.14	4.40	4.39	5.16	3.97	5.37
Men							
	Average	9.00	3.63	5.13	5.69	4.42	4.49
	Std. Dev.	8.52	4.21	6.04	6.33	5.81	4.98
Diff(%)							
	Average	-55.38	14.99	-25.57	-22.26	-16.52	-6.37

Note: Data extracted from the Annual Social and Economic Supplement (March Supplement) of the CPS for the years 1995 and 2005. In each education label the sample includes individuals who are white and 30 to 55 years old.

Table 4.2: Maximum Likelihood Estimation Results (Entire Sample) - Structural Parameters

	Master and PhD		College		High School	
	1995	2005	1995	2005	1995	2005
$\lambda_M$	0.1119 (0.0457)	0.2781 (0.0803)	0.1965 (0.0342)	0.1798 (0.0243)	0.2298 (0.0204)	0.2299 (0.0202)
$\lambda_W$	0.2906 (0.1355)	0.3003 (0.1249)	0.2731 (0.0410)	0.2345 (0.0324)	0.2869 (0.0304)	0.2493 (0.0246)
$\eta_M$	0.0017 (0.0010)	0.0082 (0.0034)	0.0056 (0.0014)	0.0071 (0.0014)	0.0154 (0.0020)	0.0150 (0.0019)
$\eta_W$	0.0041 (0.0026)	0.0049 (0.0023)	0.0110 (0.0023)	0.0086 (0.0017)	0.0134 (0.0020)	0.0136 (0.0019)
$\mu_M$	3.7536 (0.0290)	3.8622 (0.0335)	3.5851 (0.0184)	3.6000 (0.0193)	3.2107 (0.0135)	3.1833 (0.0152)
$\sigma_M$	0.5587 (0.0220)	0.6426 (0.0258)	0.5983 (0.0140)	0.6499 (0.0152)	0.5477 (0.0105)	0.5910 (0.0120)
$\mu_W$	3.6618 (0.0374)	3.6937 (0.0518)	3.5879 (0.1058)	3.4058 (0.0411)	3.0319 (0.1003)	2.9675 (0.0459)
$\sigma_W$	0.4289 (0.0246)	0.4931 (0.0378)	0.4607 (0.0398)	0.6153 (0.0253)	0.4876 (0.0390)	0.5563 (0.0236)
$p$	0.1506 (0.0469)	0.2117 (0.1079)	0.7584 (0.2790)	0.1231 (0.1391)	0.9999 (0.0039)	0.2811 (0.2609)
$k$	1.3796 (3.8471)	1.3796 (3.8471)	0.2513 (0.0679)	0.2513 (0.0679)	0.1399 (0.0763)	0.1399 (0.0763)
$w_M^*$	10.8382	10.8800	8.5801	10.0000	7.6605	8.0000
$w_W^*$	8.9373	10.0713	6.4249	7.2500	5.5156	6.0000
$\ln L$	-6142		-19721		-26548	
$N$	1572		5181		7961	

Note: Asymptotic standard errors in parentheses. Joint estimation on all years by education level.

Table 4.3: Maximum Likelihood Estimation Results (Married) - Structural Parameters

	Master and PhD		College		High School	
	1995	2005	1995	2005	1995	2005
$\lambda_M$	0.0534 (0.0378)	0.2798 (0.0885)	0.2062 (0.0404)	0.1975 (0.0305)	0.2539 (0.0251)	0.2649 (0.0269)
$\lambda_W$	0.2312 (0.1220)	0.2082 (0.1275)	0.3018 (0.0477)	0.2256 (0.0347)	0.2873 (0.0316)	0.2503 (0.0256)
$\eta_M$	0.0003 (0.0003)	0.0077 (0.0034)	0.0054 (0.0015)	0.0068 (0.0015)	0.0155 (0.0022)	0.0150 (0.0022)
$\eta_W$	0.0031 (0.0022)	0.0021 (0.0013)	0.0126 (0.0028)	0.0076 (0.0016)	0.0135 (0.0021)	0.0141 (0.0021)
$\mu_M$	3.7581 (0.0314)	3.8349 (0.0396)	3.6079 (0.0196)	3.6389 (0.0197)	3.2447 (0.0136)	3.2280 (0.0153)
$\sigma_M$	0.5557 (0.0241)	0.6734 (0.0312)	0.5932 (0.0149)	0.6303 (0.0154)	0.5251 (0.0106)	0.5719 (0.0120)
$\mu_W$	3.6321 (0.0423)	3.6891 (0.0598)	3.5690 (0.1208)	3.3913 (0.0450)	2.9446 (0.0950)	2.9363 (0.0154)
$\sigma_W$	0.4497 (0.0312)	0.4867 (0.0604)	0.4702 (0.0443)	0.6191 (0.0278)	0.5168 (0.0402)	0.5696 (0.0121)
$p$	0.1208 (0.0875)	0.2398 (0.2045)	0.7242 (0.3361)	0.1074 (0.1480)	0.9998 (0.0189)	0.0003 (0.0121)
$k$	1.5765 (6.9760)	1.5765 (6.9760)	0.2731 (0.0803)	0.2731 (0.0803)	0.0718 (0.0626)	0.0718 (0.0626)
$w_M^*$	11.8227	12.5000	8.9373	10.2427	10.8382	10.8800
$w_W^*$	9.2520	10.0750	6.6678	7.4010	8.9373	10.0713
$\ln L$	-5309		-17222		-23545	
$N$	1365		4532		7086	

Note: Asymptotic standard errors in parentheses. Joint estimation on all years by education level.

Table 4.4: Maximum Likelihood Estimation Results (Married with Children) - Structural Parameters

	Master and PhD		College		High School	
	1995	2005	1995	2005	1995	2005
$\lambda_M$	0.0534 (0.0378)	0.2798 (0.0885)	0.2062 (0.0404)	0.1975 (0.0305)	0.2539 (0.0251)	0.2649 (0.0269)
$\lambda_W$	0.2312 (0.1220)	0.2082 (0.1275)	0.3018 (0.0477)	0.2256 (0.0347)	0.2873 (0.0316)	0.2503 (0.0256)
$\eta_M$	0.0003 (0.0003)	0.0077 (0.0034)	0.0054 (0.0015)	0.0068 (0.0015)	0.0155 (0.0022)	0.0150 (0.0022)
$\eta_W$	0.0031 (0.0022)	0.0021 (0.0013)	0.0126 (0.0028)	0.0076 (0.0016)	0.0135 (0.0021)	0.0141 (0.0021)
$\mu_M$	3.7581 (0.0314)	3.8349 (0.0396)	3.6079 (0.0196)	3.6389 (0.0197)	3.2447 (0.0136)	3.2280 (0.0153)
$\sigma_M$	0.5557 (0.0241)	0.6734 (0.0312)	0.5932 (0.0149)	0.6303 (0.0154)	0.5251 (0.0106)	0.5719 (0.0120)
$\mu_W$	3.6321 (0.0423)	3.6891 (0.0598)	3.5690 (0.1208)	3.3913 (0.0450)	2.9446 (0.0950)	2.9363 (0.0154)
$\sigma_W$	0.4497 (0.0312)	0.4867 (0.0604)	0.4702 (0.0443)	0.6191 (0.0278)	0.5168 (0.0402)	0.5696 (0.0121)
$p$	0.1208 (0.0875)	0.2398 (0.2045)	0.7242 (0.3361)	0.1074 (0.1480)	0.9998 (0.0189)	0.0003 (0.0121)
$k$	1.5765 (6.9760)	1.5765 (6.9760)	0.2731 (0.0803)	0.2731 (0.0803)	0.0718 (0.0626)	0.0718 (0.0626)
$w_M^*$	11.8227	12.5000	8.9373	10.2427	10.8382	10.8800
$w_W^*$	9.2520	10.0750	6.6678	7.4010	8.9373	10.0713
$\ln L$	-5309		-17222		-23545	
$N$	1365		4532		7086	

Note: Asymptotic standard errors in parentheses. Joint estimation on all years by education level.

Table 4.5: Estimation Results - Predicted Productivity and Wages

	Master and PhD		College		High School	
	1995	2005	1995	2005	1995	2005
Men						
Productivity						
Average	49.88 (1.509)	58.48 (2.052)	43.12 (0.828)	45.20 (0.876)	28.81 (0.393)	28.73 (0.422)
Variance	911.33 (113.068)	1748.68 (241.048)	800.26 (61.566)	1074.05 (82.764)	290.35 (16.632)	345.02 (20.879)
Offered Earnings						
Average	30.36 (0.754)	34.68 (1.026)	25.85 (0.414)	27.60 (0.438)	18.24 (0.196)	18.36 (0.211)
Accepted Earnings						
Average	30.50 (0.753)	34.95 (1.028)	26.00 (0.414)	28.04 (0.437)	18.42 (0.194)	18.72 (0.207)
Woman						
Productivity						
Average	42.68 (1.485)	45.39 (2.210)	40.21 (3.587)	36.42 (1.091)	23.35 (1.916)	22.70 (0.796)
Variance	367.94 (50.505)	567.13 (113.378)	382.25 (33.931)	610.60 (49.093)	146.42 (8.280)	186.91 (11.983)
Offered Earnings						
Average	25.03 (2.600)	25.92 (5.538)	20.20 (0.777)	21.75 (1.202)	12.42 (0.213)	14.19 (0.817)
Average at Prejudiced	20.63 (15.127)	19.19 (24.569)	19.21 (0.378)	21.14 (0.702)	12.42 (0.213)	13.78 (0.600)
Average at Unprejudiced	25.81 (0.742)	27.73 (1.105)	23.31 (1.794)	21.84 (0.546)	14.44 (0.958)	14.35 (0.398)
Accepted Earnings						
Average	24.53 (1.711)	26.44 (3.453)	19.77 (0.369)	21.66 (0.325)	12.88 (0.204)	14.17 (0.162)
Average at Prejudiced	17.32 (9.401)	21.46 (16.124)	18.64 (1.169)	19.31 (0.503)	12.88 (0.204)	13.32 (0.503)
Average at Unprejudiced	25.81 (0.740)	27.78 (1.092)	23.32 (1.790)	21.99 (0.493)	14.47 (0.913)	14.51 (0.332)

Notes: The table reported predicted values based on the Maximum Likelihood estimated structural parameters. Estimated parameters are reported in Table 4.2. Asymptotic standard errors by Delta method in parentheses.



Table 4.6: Estimation Results - Predicted Labor Market Dynamics

	Master and PhD		College		High School	
	1995	2005	1995	2005	1995	2005
Men						
Hazard Rate out of Unemployment						
Overall	0.1111 (0.0454)	0.2751 (0.0794)	0.1948 (0.0339)	0.1757 (0.0237)	0.2261 (0.0201)	0.2228 (0.0195)
To a Prejudiced	0.0167 (0.0086)	0.0582 (0.0341)	0.1478 (0.0601)	0.0216 (0.0246)	0.2261 (0.0201)	0.0626 (0.0584)
To an Unprejudiced	0.0943 (0.0389)	0.2169 (0.0693)	0.0471 (0.0550)	0.1541 (0.0321)	0.00001 (0.0009)	0.1602 (0.0598)
Hazard Rate out of Employment						
Overall	0.0017 (0.0010)	0.0082 (0.0034)	0.0056 (0.0014)	0.0071 (0.0014)	0.0154 (0.0020)	0.0150 (0.0019)
Labor Market Status						
Emp. Rate at Prejudiced	0.1483 (0.0462)	0.2056 (0.1048)	0.7371 (0.2712)	0.1183 (0.1337)	0.9362 (0.0066)	0.2634 (0.2445)
Emp. Rate at Unprejudiced	0.8367 (0.0465)	0.7655 (0.1050)	0.2348 (0.2712)	0.8429 (0.1338)	0.0001 (0.0036)	0.6736 (0.2445)
Unemployment Rate	0.0150 (0.0061)	0.0289 (0.0082)	0.0281 (0.0048)	0.0388 (0.0051)	0.0637 (0.0055)	0.0630 (0.0053)
Woman						
Hazard Rate out of Unemployment						
Overall	0.2491 (0.1114)	0.2393 (0.0798)	0.2619 (0.0390)	0.2261 (0.0308)	0.2709 (0.0282)	0.2380 (0.0231)
To a Prejudiced	0.0023 (0.0271)	0.0031 (0.0315)	0.1959 (0.0823)	0.0226 (0.0273)	0.2709 (0.0283)	0.0619 (0.0620)
To an Unprejudiced	0.2468 (0.1136)	0.2361 (0.0848)	0.0660 (0.0776)	0.2035 (0.0388)	0.00002 (0.0011)	0.1761 (0.0640)
Hazard Rate out of Employment						
Overall	0.0041 (0.0026)	0.0049 (0.0023)	0.0110 (0.0023)	0.0086 (0.0017)	0.0134 (0.0020)	0.0136 (0.0019)
Labor Market Status						
Emp. Rate at Prejudiced	0.0092 (0.1070)	0.0128 (0.1287)	0.7179 (0.2821)	0.0963 (0.1157)	0.9527 (0.0062)	0.2459 (0.2451)
Emp. Rate at Unprejudiced	0.9747 (0.1072)	0.9670 (0.1294)	0.2418 (0.2821)	0.8671 (0.1161)	0.0001 (0.0039)	0.6999 (0.2452)
Unemployment Rate	0.0161 (0.0071)	0.0202 (0.0123)	0.0403 (0.0059)	0.0366 (0.0108)	0.0472 (0.0048)	0.0542 (0.0090)

Notes: The table reported predicted values based on the Maximum Likelihood estimated structural parameters. Estimated parameters are reported in Table 4.2. Asymptotic standard errors by Delta method in parentheses.

Table 4.7: Wage Gap Decomposition - Woman/men ratio on average accepted wage

Gap Generated by:	1995				2005			
	Overall	Top 50%	Top 25%	Top 10%	Overall	Top 50%	Top 25%	Top 10%
Master and PhD								
Productivity	0.835	0.883	0.865	0.857	0.699	1.628	1.344	1.130
Prejudiced	0.935	0.958	0.971	0.982	0.881	0.923	0.950	0.974
Search Frictions	1.337	1.195	1.139	1.088	1.052	1.031	1.021	1.013
All Parameters	0.804	0.867	0.853	0.849	0.756	0.857	0.841	0.834
Sample	0.823	0.791	0.793	0.812	0.728	0.682	0.638	0.568
College								
Productivity	0.911	0.937	0.911	0.892	0.758	0.827	0.838	0.857
Prejudiced	0.801	0.862	0.898	0.931	0.976	0.984	0.988	0.993
Search Frictions	1.116	1.073	1.054	1.036	1.106	1.066	1.047	1.030
All Parameters	0.760	0.824	0.824	0.828	0.773	0.837	0.846	0.862
Sample	0.779	0.779	0.775	0.797	0.794	0.793	0.806	0.869
High School								
Productivity	0.769	0.777	0.772	0.770	0.742	0.766	0.771	0.780
Prejudiced	0.853	0.888	0.910	0.932	0.964	0.974	0.980	0.985
Search Frictions	1.091	1.063	1.050	1.038	1.036	1.025	1.019	1.014
All Parameters	0.699	0.718	0.723	0.731	0.757	0.776	0.779	0.787
Sample	0.701	0.711	0.724	0.745	0.763	0.763	0.778	0.793

Notes: Women/men ratio on average accepted earnings computed over the entire distribution and over the top 50%, the top 75% and the top 10%. All counterfactuals are generated taking into account equilibrium effects.

Table 4.8: Wage Gap Decomposition Conditioning on Marital Status and Children - Woman/men ratio on average accepted wage

Gap Generated by:	1995			2005		
	Entire Sample	Married	Married with Kids	Entire Sample	Married	Married with Kids
Master and PhD						
Productivity	0.835	0.835	0.884	0.699	0.698	0.874
Prejudiced	0.935	0.964	0.960	0.881	0.878	0.812
Search Frictions	1.337	1.387	1.373	1.052	0.895	1.064
All Parameters	0.804	0.793	0.778	0.756	0.727	0.729
Sample	0.823	0.820	0.809	0.728	0.700	0.752
College						
Productivity	0.911	0.872	0.754	0.758	0.719	0.735
Prejudiced	0.801	0.795	0.877	0.976	0.976	0.984
Search Frictions	1.116	1.135	1.072	1.106	1.051	1.070
All Parameters	0.760	0.737	0.736	0.773	0.753	0.751
Sample	0.779	0.758	0.753	0.794	0.774	0.775
High School						
Productivity	0.769	0.697	0.628	0.742	0.701	0.666
Prejudiced	0.853	0.933	0.794	0.964	1.000	0.937
Search Frictions	1.091	1.049	1.126	1.036	0.982	0.941
All Parameters	0.699	0.744	0.646	0.757	0.818	0.721
Sample	0.701	0.683	0.652	0.763	0.748	0.727

Note: Women/men ratio on average accepted earnings computed over the entire distribution. All counterfactuals are generated taking into account equilibrium effects.

Table 4.9: Welfare Returns to Schooling - Ratio of Average Welfare Measures

	1995		2005	
	MA and PhD / College	MA and PhD High School	MA and PhD / College	MA and PhD High School
Overall				
All Parameters	1.268	1.925	1.238	1.926
Without Prejudiced	1.177	1.840	1.314	2.032
Men				
All Parameters	1.215	1.824	1.240	1.941
Without Prejudiced	..	..	..	..
Women				
All Parameters	1.307	2.007	1.242	1.944
Without Prejudiced	1.120	1.832	1.406	2.167
		Entire Sample		
Overall				
All Parameters	1.311	2.026	1.242	1.999
Without Prejudiced	1.259	1.863	1.379	2.168
Men				
All Parameters	1.224	1.812	1.201	1.930
Without Prejudiced	..	..	..	..
Women				
All Parameters	1.372	2.219	1.274	2.079
Without Prejudiced	1.261	1.849	1.608	2.481
		Married with Children:		

Notes: The table presents ratio of the average welfare measures of the corresponding education levels. Welfare measures are computed using the estimated structural parameters. See main text for the complete definition. Married with Children means married and with children younger than 18 years old.

Table 4.10: Policy Experiments - Relative Average Welfare Measures

	1995			2005		
	All Parameters	Equal Pay	Affirmative Action	All Parameters	Equal Pay	Affirmative Action
Entire Sample						
Master and PhD						
Men	1.0000	0.9459	0.9861	1.0000	0.9149	0.9799
Women	0.7857	0.8088	0.8067	0.7659	0.7656	0.7841
Overall	0.9063	0.8860	0.9076	0.8787	0.8376	0.8785
College						
Men	1.0000	0.9111	0.9826	1.0000	0.9678	0.9830
Women	0.7299	0.8250	0.7487	0.7650	0.7950	0.7827
Overall	0.8684	0.8691	0.8686	0.8802	0.8797	0.8809
High School						
Men	1.0000	0.9202	0.9816	1.0000	0.9624	0.9827
Women	0.7138	0.7985	0.7327	0.7650	0.8040	0.7837
Overall	0.8586	0.8601	0.8586	0.8856	0.8853	0.8858
Married with Children						
Master and PhD						
Men	1.0000	0.9653	0.9900	1.0000	0.9108	0.9825
Women	0.7618	0.8401	0.7836	0.7703	0.8737	0.7896
Overall	0.9035	0.9146	0.9064	0.8895	0.8929	0.8897
College						
Men	1.0000	0.9360	0.9816	1.0000	0.9669	0.9834
Women	0.6794	0.7337	0.6984	0.7265	0.7570	0.7435
Overall	0.8432	0.8371	0.8431	0.8604	0.8598	0.8610
High School						
Men	1.0000	0.8605	0.9797	1.0000	0.9323	0.9806
Women	0.6222	0.6696	0.6409	0.7151	0.7495	0.7332
Overall	0.8084	0.7637	0.8079	0.8588	0.8417	0.8580

Notes: The table reports average welfare normalized with respect to men in the Benchmark Model. Benchmark Model is the model at the estimated parameters. Equal Pay means each employer must pay one wage at same productivity. Affirmative Action means employers receive a flow subsidy equal to 5% of the men average accepted wage when hiring a woman and the subsidy is financed by a lump-sum tax on all workers. . Married with Children means married and with children younger than 18 years old.

Figure 4.1: Gender Gap in Percentage of Graduates by Cohort

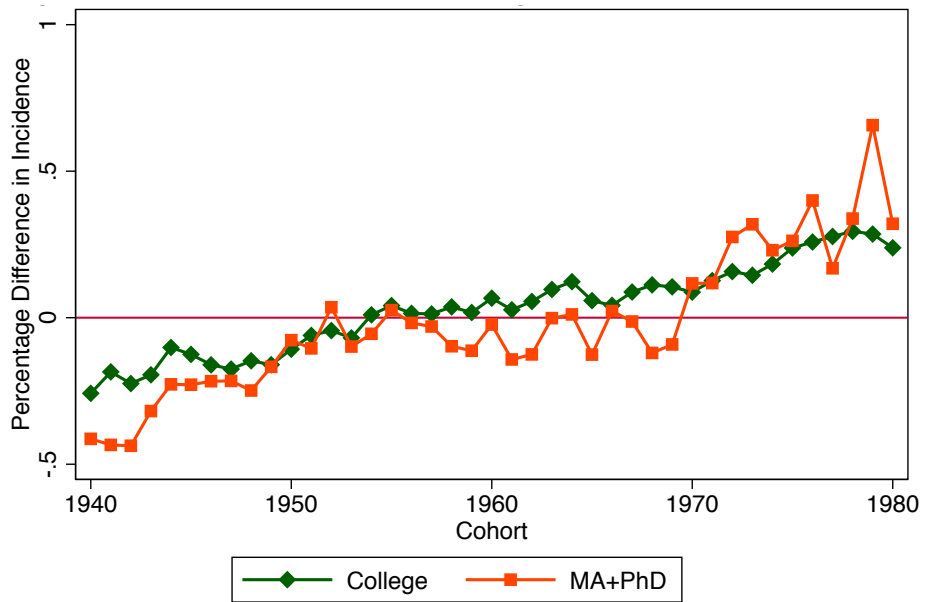
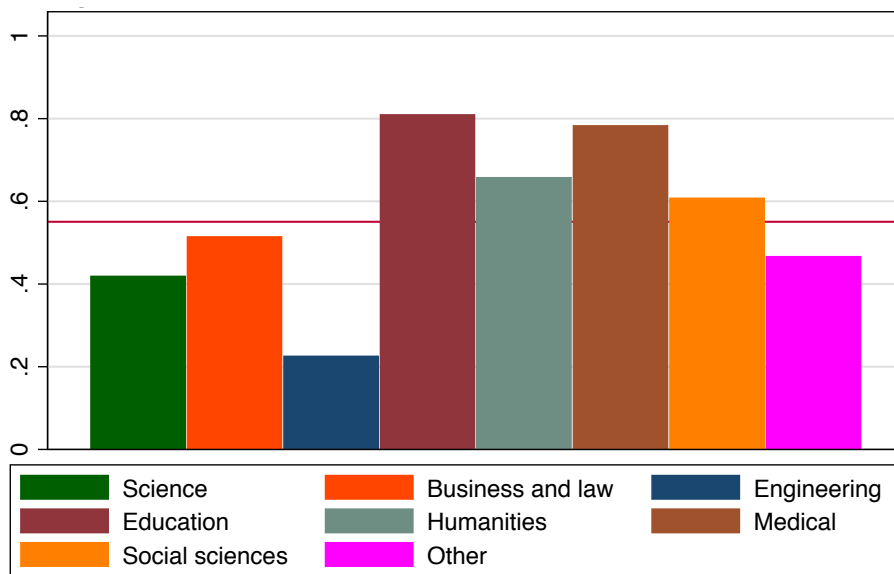


Figure 4.2: Proportion of Women in Field of Study (2002)



Note: 30-45 years old.

Figure 4.3: Majors with Flexible Jobs (2002)

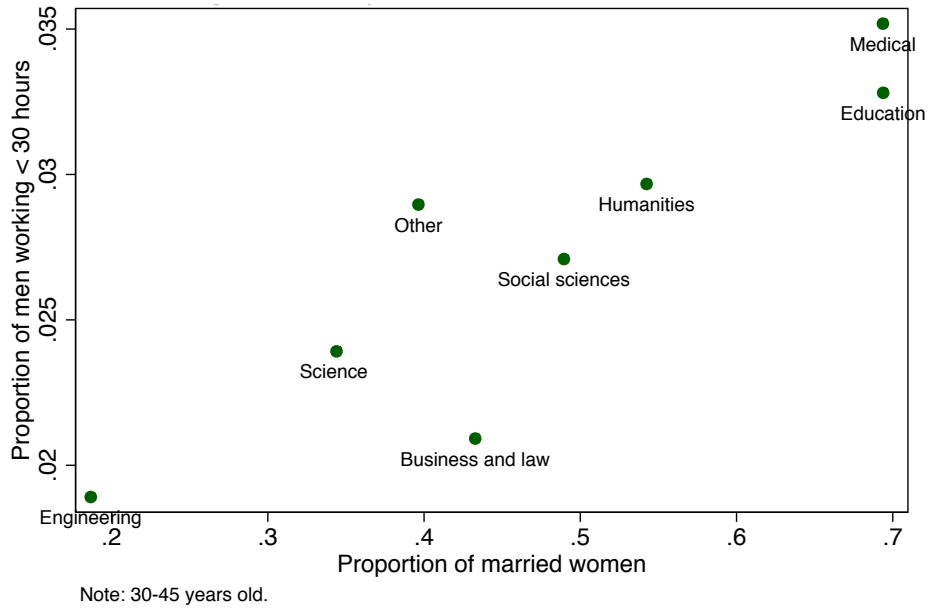


Figure 4.4: Participation Rates by Gender and Education Level (Percentage of Relevant Group in Adult Civilian Population)

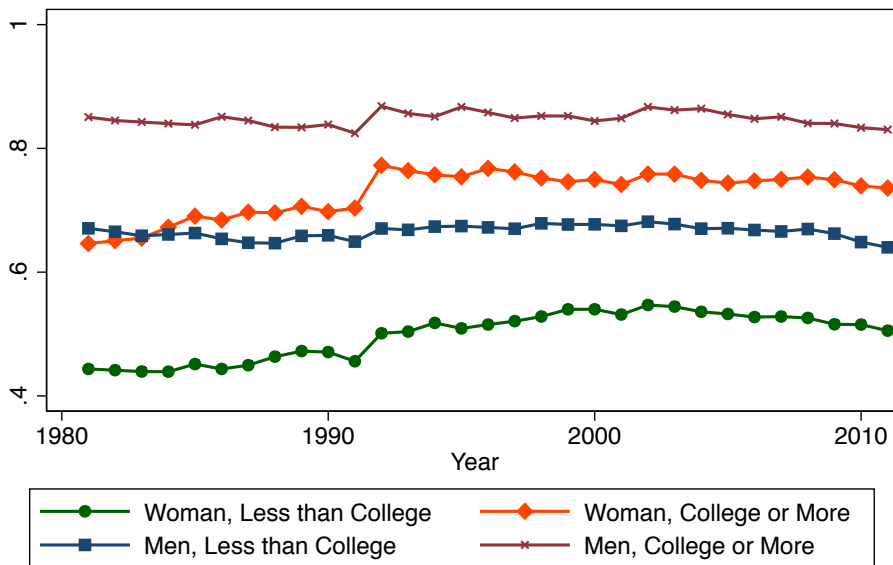


Figure 4.5: Employment Rates by Gender and Education Level (Percentage of Relevant Group in Labour Force)

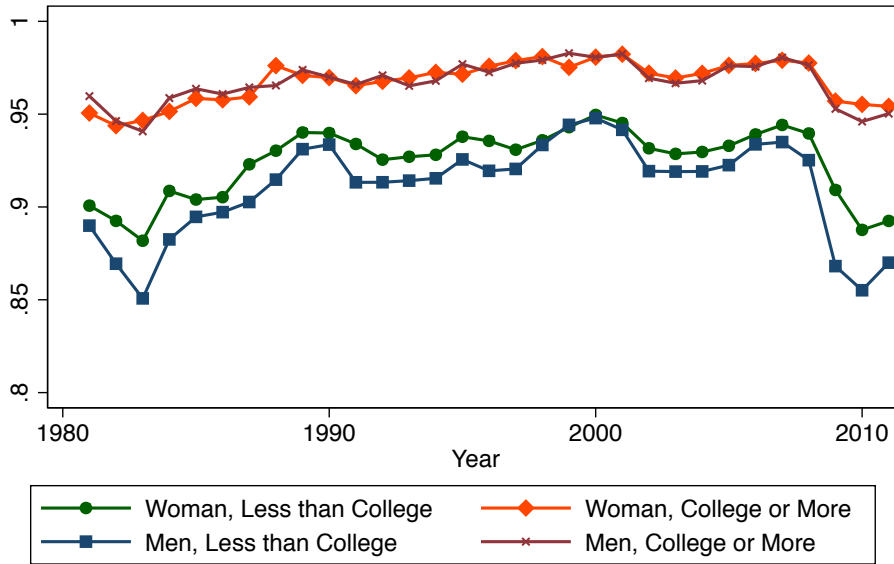


Figure 4.6: Gender Gaps in Part Time Occupations (Men vs. Women with Part Time Jobs)

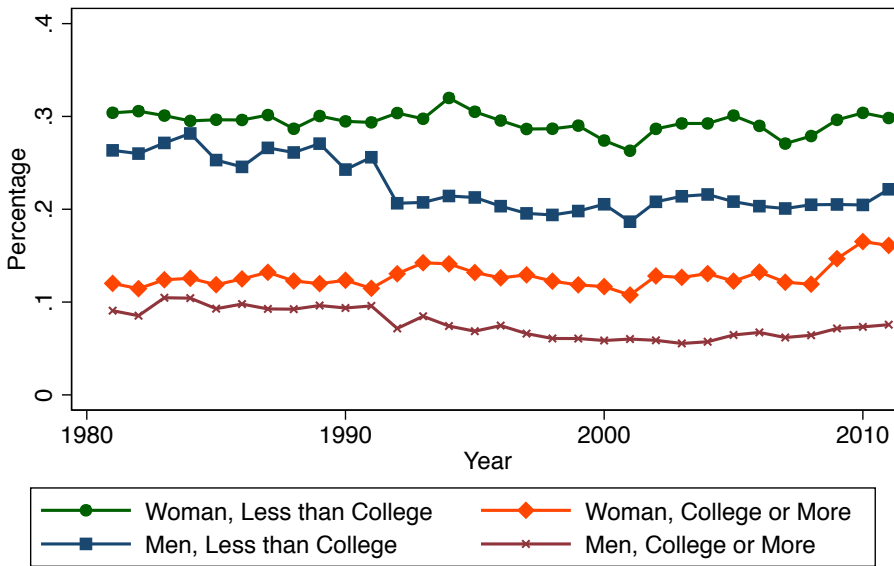




Figure 4.7: Gender Earnings Differential Over Time, Unconditional Case (Point estimates and 95% confidence interval)

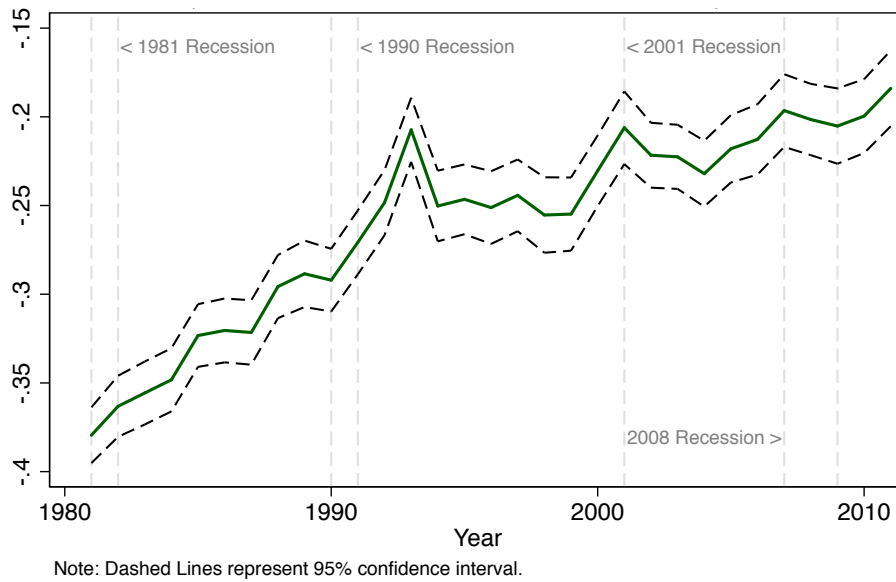


Figure 4.8: Gender Earnings Differential Over Time, Conditional Case (Point estimates and 95% confidence interval)

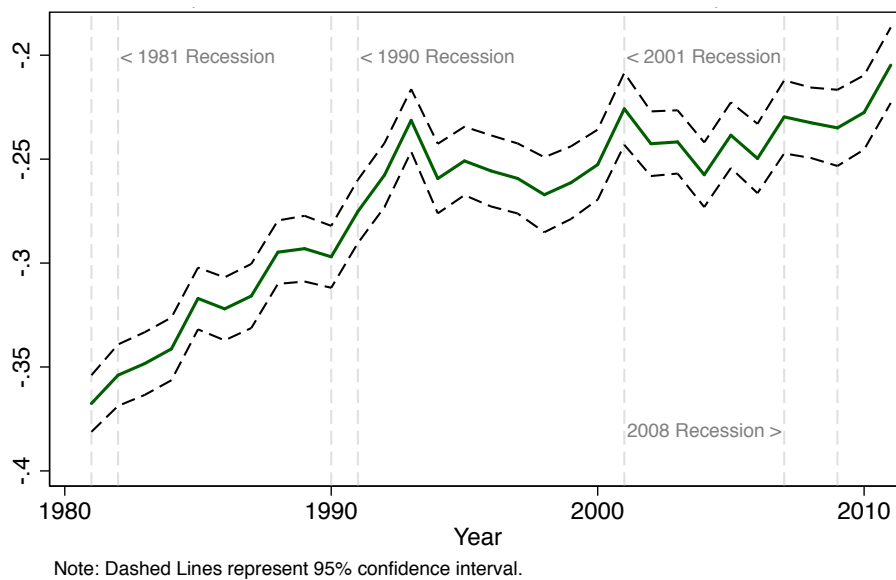


Figure 4.9: Gender Gap in Log Hourly Earnings by Percentile and Year (Unconditional Case)

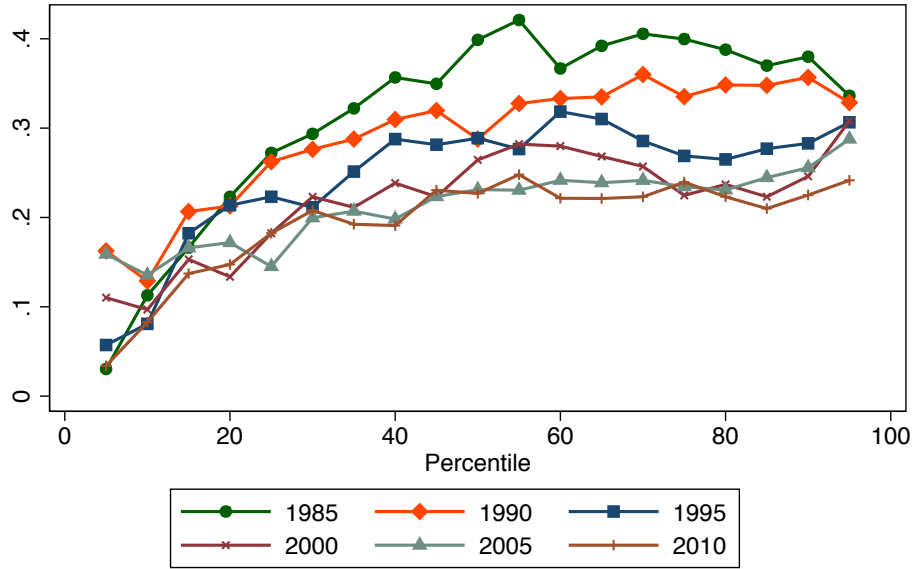


Figure 4.10: Gender Composition of Managerial Occupations (Proportion of Women)

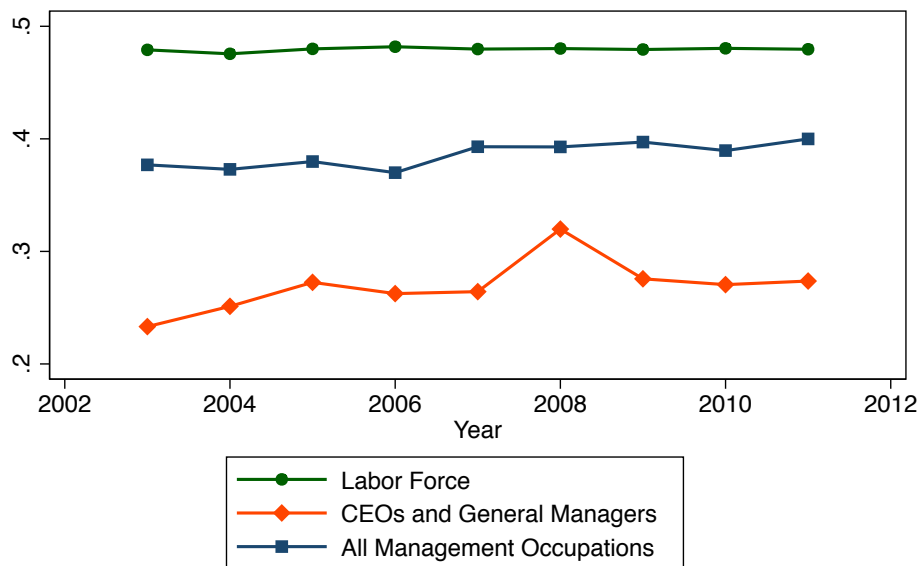
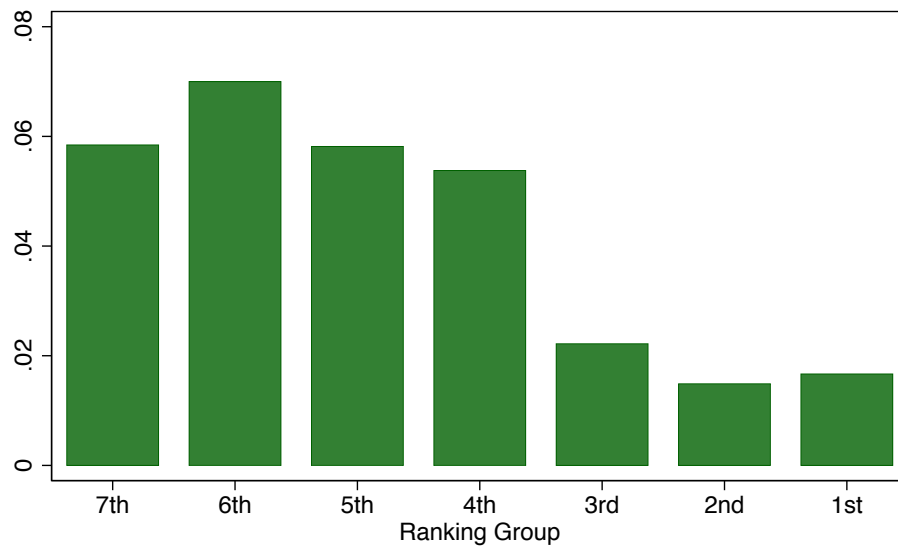


Figure 4.11: Positions within CEOs and General Managers (Proportion of Women)



Note: Gayl, Golan and Miller (2009), Table 1.

## APPENDIX A

### APPENDIX TO CHAPTER 1

#### A.1 VALUE FUNCTIONS EXPRESSED IN TERMS OF THE TOTAL SURPLUS

The worker's flow value of unemployment, written in terms of the total surplus, is:

$$rU = b + \alpha_w^P \beta_P \int_{x_{OP}^*}^{\infty} S_{OP}(x) f_P(x) dx + \alpha_w^T \beta_T \int_{x_T^*}^{\infty} S_T(x) f_T(x) dx$$

The worker's flow value of employment, written in terms of the total surplus, are:

$$\begin{aligned} S_{OP}(x) &= \frac{w_{OP}(x)(1 - \tau_P) - rU + \lambda_P \beta_P \int_{x_{IP}}^{\infty} S_{IP}(x') f_P(x') dx'}{(r + \lambda_P) \beta_P} \\ S_{IP}(x) &= \frac{w_{IP}(x)(1 - \tau_P) - rU + \lambda_P \beta_P \int_{x_{IP}}^{\infty} S_{IP}(x') f_P(x') dx'}{(r + \lambda_P) \beta_P} \\ S_T(x) &= \frac{w_T(x)(1 - \tau_T) - rU}{(r + \lambda_T) \beta_T} \end{aligned}$$

The firm's flow value of a filled vacancy, written in terms of the total surplus, are:

$$\begin{aligned} S_{OP}(x) &= \frac{x - w_{OP}(x)(1 + \phi_P) + \lambda_P(1 - \beta_P) \frac{(1 + \phi_P)}{(1 - \tau_P)} \int_{x_{IP}}^{\infty} S_{IP}(x') f_P(x') dx' - \lambda_P \Psi \left( \frac{1 - \tau_P}{1 + \phi_P} \right)}{(r + \lambda_P)(1 - \beta_P)} \\ S_{IP}(x) &= \frac{x - w_{IP}(x)(1 + \phi_P) + \lambda_P(1 - \beta_P) \frac{(1 + \phi_P)}{(1 - \tau_P)} \int_{x_{IP}}^{\infty} S_{IP}(x') f_P(x') dx' + r \Psi \left( \frac{1 - \tau_P}{1 + \phi_P} \right)}{(r + \lambda_P)(1 - \beta_P)} \\ S_T(x) &= \frac{x - w_T(x)(1 + \phi_T)}{(r + \lambda_T)(1 - \beta_T)} \left( \frac{1 - \tau_T}{1 + \phi_T} \right) \end{aligned}$$

The firm's flow value of an unfilled vacancy, written in terms of the total surplus, are

(using the free entry condition  $V_T = V_P = 0$ ):

$$\begin{aligned} k_P &= \alpha_e^P (1 - \beta_P) \frac{(1 + \phi_P)}{(1 - \tau_P)} \int_{x_{OP}}^{\infty} S_{OP}(x) f_P(x) dx \\ k_T &= \alpha_e^T (1 - \beta_T) \frac{(1 + \phi_T)}{(1 - \tau_T)} \int_{x_T}^{\infty} S_T(x) f_T(x) dx \end{aligned}$$

## A.2 COMPUTATIONAL ALGORITHM

This appendix presents the algorithm to computationally implement the model. The algorithm is essentially a fixed point algorithm on  $\eta$  and  $q$ , which exploits the recursive nature of the model in these two endogenous variables. The algorithm is as follows:

1. Guess values for  $\eta^0$  and  $q^0$  (note that  $\alpha_w^P = m[\eta q]$ ,  $\alpha_w^T = m[(1-\eta)q]$ ,  $\alpha_e^P = \frac{m[\eta q]}{\eta q}$  and  $\alpha_e^T = \frac{m[(1-\eta)q]}{(1-\eta)q}$ ). Calculate:

$$rU = b + \left( \frac{1 - \tau_P}{1 + \phi_P} \right) \frac{\eta q \beta_P k_P}{(1 - \beta_P)} + \left( \frac{1 - \tau_T}{1 + \phi_T} \right) \frac{(1 - \eta) q \beta_T k_T}{(1 - \beta_T)}$$

2. Given  $rU$  iterate the following bellman equations to find the fixed point on  $x_{IP}^*$ .  
Guess  $x_{IP}^{*,0}$  and update:

$$x_{IP}^{*,n} = \frac{(1 + \phi_P)}{(1 - \tau_P)} rU - r\Psi - \frac{\lambda_P}{r + \lambda_P} \int_{x_{IP}^{*,n-1}}^{\infty} (x' - x_{IP}^{*,n-1}) f_P(x') dx'$$

3. Given  $x_{IP}^*$  and  $rU$  calculate:

$$\begin{aligned} x_{OP}^* &= x_{IP}^* + (\lambda_P + r) \Psi \\ x_T^* &= \frac{(1 + \phi_T)}{(1 - \tau_T)} rU \end{aligned}$$

4. Given  $x_{OP}^*$  and  $x_T^*$  calculate  $\eta^1$  and  $q^1$  solving the following system of equations:

$$\begin{aligned} k_P &= \frac{m[\eta q]}{\eta q} \frac{(1 - \beta_P)}{(r + \lambda_P)} \int_{x_{OP}^*}^{\infty} (x - x_{OP}^*) f_P(x) dx \\ k_T &= \frac{m[(1 - \eta) q]}{(1 - \eta) q} \frac{(1 - \beta_T)}{(r + \lambda_T)} \int_{x_T^*}^{\infty} (x - x_T^*) f_T(x) dx \end{aligned}$$

For a Cobb-Douglas matching function ( $m[x] = x^\gamma$ ) we have:

$$q = (\Xi_T)^{\frac{1}{\gamma-1}} + (\Xi_P)^{\frac{1}{\gamma-1}} \quad \eta = \frac{(\Xi_P)^{\frac{1}{\gamma-1}}}{(\Xi_T)^{\frac{1}{\gamma-1}} + (\Xi_P)^{\frac{1}{\gamma-1}}}$$

where:

$$\begin{aligned}\Xi_P &= k_P \div \frac{(1 - \beta_P)}{(r + \lambda_P)} \int_{x_{OP}^*}^{\infty} (x - x_{OP}^*) f_P(x) dx \\ \Xi_T &= k_T \div \frac{(1 - \beta_T)}{(r + \lambda_T)} \int_{x_T^*}^{\infty} (x - x_T^*) f_T(x) dx\end{aligned}$$

5. If  $|q^0 - q^1| < \varepsilon^q$  and  $|\eta^0 - \eta^1| < \varepsilon^\eta$  then we have a solution, otherwise update  $q^{new} = q^0 + \theta^q (q^0 - q^1)$  and  $\eta^{new} = \eta^0 + \theta^\eta (\eta^0 - \eta^1)$  and return to step 1.  $\varepsilon^i$  and  $\theta^i$ , for  $i = q, \eta$ , are the tolerance level and the step size, respectively.

### A.3 WAGES CONTRIBUTION TO THE LIKELIHOOD FUNCTION

To find the wages distribution conditional on the model, the first step is to map the productivity distribution for each type of contract into an unconditional wages distribution. First, mapping the productivity distribution to a wage distribution for a new hire with permanent contract (outsider) gives:

$$\begin{aligned}
G(w_i|OP) &= \Pr(W \leq w_i|OP) \\
&= \Pr\left(\frac{\beta_P(x - \lambda_P\Psi) + (1 - \beta_P)\frac{(1+\phi_P)}{(1-\tau_P)}rU}{(1 + \phi_P)} \leq w_i|OP\right) \\
&= \Pr\left(x \leq w_i\frac{(1 + \phi_P)}{\beta_P} - \frac{(1 - \beta_P)(1 + \phi_P)}{\beta_P(1 - \tau_P)}rU + \lambda_P\Psi|OP\right) \\
&= F_P\left(w_i\frac{(1 + \phi_P)}{\beta_P} - \frac{(1 - \beta_P)(1 + \phi_P)}{\beta_P(1 - \tau_P)}rU + \lambda_P\Psi\right)
\end{aligned}$$

Second, the wages distribution for continuing employees with permanent contracts (insiders) that result from the same mapping is:

$$\begin{aligned}
G(w_i|P, IP) &= \Pr(W \leq w_i|IP) \\
&= \Pr\left(\frac{\beta_P(x + r\Psi) + (1 - \beta_P)\frac{(1+\phi_P)}{(1-\tau_P)}rU}{(1 + \phi_P)} \leq w_i|IP\right) \\
&= \Pr\left(x \leq w_i\frac{(1 + \phi_P)}{\beta_P} - \frac{(1 - \beta_P)(1 + \phi_P)}{\beta_P(1 - \tau_P)}rU - r\Psi|IP\right) \\
&= F_P\left(w_i\frac{(1 + \phi_P)}{\beta_P} - \frac{(1 - \beta_P)(1 + \phi_P)}{\beta_P(1 - \tau_P)}rU - r\Psi\right)
\end{aligned}$$

Finally, in the case of a temporary job, the mapping gives:

$$\begin{aligned}
G(w_i|T) &= \Pr(W \leq w_i|T) \\
&= \Pr\left(\frac{\beta_Tx + (1 - \beta_T)\frac{(1+\phi_T)}{(1-\tau_T)}rU}{(1 + \phi_T)} \leq w_i|T\right) \\
&= \Pr\left(x \leq \frac{(1 + \phi_T)}{\beta_T}w_i - \frac{(1 - \beta_T)(1 + \phi_T)}{\beta_T(1 - \tau_T)}rU|T\right) \\
&= F_T\left(\frac{(1 + \phi_T)}{\beta_T}w_i - \frac{(1 - \beta_T)(1 + \phi_T)}{\beta_T(1 - \tau_T)}rU\right)
\end{aligned}$$

Note that in the data the distributions of accepted wages are observed. These distributions, conditional on the model, are truncations of the the above unconditional wages distributions and the truncation point is the reservations wage (this value is also a mapping from the reservation productivity using wages equations). Conditioning on wages above the reservation value and taking into account that wages are observed only for those who are employed, the following is obtained:

$$g(w_i|w_i > w_{OP}(x_{OP}^*), OP, i \in E_P) = \frac{\frac{(1+\phi_P)}{\beta_P} f_P \left( w_i \frac{(1+\phi_P)}{\beta_P} - \frac{(1-\beta_P)}{\beta_P} \frac{(1+\phi_P)}{(1-\tau_P)} rU + \lambda_P \Psi \right)}{1 - G(w_{OP}(x_{OP}^*)|OP)}$$

$$g(w_i|w_i > w_{IP}(x_{IP}^*), IP, i \in E_P) = \frac{\frac{(1+\phi_P)}{\beta_P} f_P \left( w_i \frac{(1+\phi_P)}{\beta_P} - \frac{(1-\beta_P)}{\beta_P} \frac{(1+\phi_P)}{(1-\tau_P)} rU - r\Psi \right)}{1 - G(w_{IP}(x_{IP}^*)|IP)}$$

$$g(w_i|w_i > w_T(x_T^*), T, i \in E_T) = \frac{\frac{(1+\phi_T)}{\beta_T} f_T \left( w_i \frac{(1+\phi_T)}{\beta_T} - \frac{(1-\beta_T)}{\beta_T} \frac{(1+\phi_T)}{(1-\tau_T)} rU \right)}{1 - G(w_T(x_T^*)|T)}$$

Removing the condition of being an employee and using the probability of having a permanent or a temporary contract (that is, the equilibrium employment rate in each type of contract) result in:

$$g(w_i, i \in E_P | w_i > w_{OP}(x_{OP}^*), OP) = \frac{\frac{(1+\phi_P)}{\beta_P} f_P \left( w_i \frac{(1+\phi_P)}{\beta_P} - \frac{(1-\beta_P)}{\beta_P} \frac{(1+\phi_P)}{(1-\tau_P)} rU + \lambda_P \Psi \right)}{1 - G(w_{OP}(x_{OP}^*)|OP)} e_{OP}$$

$$g(w_i, i \in E_P | w_i > w_{IP}(x_{IP}^*), IP) = \frac{\frac{(1+\phi_P)}{\beta_P} f_P \left( w_i \frac{(1+\phi_P)}{\beta_P} - \frac{(1-\beta_P)}{\beta_P} \frac{(1+\phi_P)}{(1-\tau_P)} rU - r\Psi \right)}{1 - G(w_{IP}(x_{IP}^*)|IP)} e_{IP}$$

$$g(w_i, i \in E_T | w_i > w_T(x_T^*), T) = \frac{\frac{(1+\phi_T)}{\beta_T} f_T \left( w_i \frac{(1+\phi_T)}{\beta_T} - \frac{(1-\beta_T)}{\beta_T} \frac{(1+\phi_T)}{(1-\tau_T)} rU \right)}{1 - G(w_T(x_T^*)|T)} e_T$$

The next step is to remove the condition of whether the worker with permanent contract is an outsider or an insider. Using the fact that  $w_{IP}(x_{IP}^*) = w_{OP}(x_{OP}^*) = w_P(x_P^*)$ , the density of permanent job's wages is:

$$g(w_i, i \in E_P | w_i > w_P(x_P^*), P) = g(w_i, i \in E | w_i > w_P(x_P^*), P, OP) \Pr(OP)$$

$$+ g(w_i, i \in E | w_i > w_P(x_P^*), P, IP) \Pr(IP)$$



where  $\Pr(OP)$  is the probability of receiving zero shocks in  $t$ . This probability depends on the duration of the job. The more the contract lasts the less likely is the fact that no productivity shocks have arrived. Conditional on the model, productivity shocks arrive at a Poisson rate  $\lambda_P$ , and therefore  $\Pr(OP) = \Pr[\text{receive 0 shocks in } t] = \exp(-\lambda_P t_{e_P})$  and  $\Pr(IP) = 1 - \Pr(OP)$ . Hence:

$$g(w_i, i \in E_P | w_i > w_P(x^*_P), P) = \left[ \frac{\exp(-\lambda_P t_{i,e_P}) \frac{(1+\phi_P)}{\beta_P} f_P \left( w_i \frac{(1+\phi_P)}{\beta_P} - \frac{(1-\beta_P)}{\beta_P} \frac{(1+\phi_P)}{(1-\tau_P)} rU + \lambda_P \Psi \right)}{1 - G(w_P(x^*_P) | P, OP)} + \frac{(1 - \exp(-\lambda_P t_{i,e_P})) \frac{(1+\phi_P)}{\beta_P} f_P \left( w_i \frac{(1+\phi_P)}{\beta_P} - \frac{(1-\beta_P)}{\beta_P} \frac{(1+\phi_P)}{(1-\tau_P)} rU - r\Psi \right)}{1 - G(w_P(x^*_P) | P, IP)} \right] e_P$$

#### A.4 PARAMETERS IDENTIFICATION IN THE LIKELIHOOD FUNCTION

Identification is formally shown by closely following Flabbi [2010a]. Recalling that the likelihood function was:

$$\begin{aligned} L(\Theta^L; w, t) &= \prod_{i=1}^N [f_u(t_{i,u}, i \in U)]^u \\ &\quad \times [g(w_i, i \in E_P | w_i > w_P(x_P^*), P)]^{e_P \times (1-u)} \\ &\quad \times [g(w_i, i \in E_T | w_i > w_T(x_T^*), T)]^{(1-e_P) \times (1-u)} \end{aligned}$$

or alternatively using logarithm:

$$\begin{aligned} \ln L(\Theta^L; w, t) &= \sum_{i \in N_u} \ln f_u(t_{i,u}, i \in U) + \sum_{i \in N_P} \ln g(w_i, i \in E_P | w_i > w_P(x_P^*), P) \\ &\quad + \sum_{i \in N_T} \ln g(w_i, i \in E_T | w_i > w_T(x_T^*), T) \end{aligned}$$

Using the contribution of unemployment duration and wages, the likelihood becomes:

$$\begin{aligned} \ln L(\Theta^L; w, t) &= \sum_{i \in N_{u,P}} \ln [h_u^P \exp(-h_u^P t_{u,i})] + \sum_{i \in N_{u,T}} \ln [h_u^T \exp(-h_u^T t_{u,i})] + \sum_{i \in N_u} \ln u \\ &\quad + \sum_{i \in N_T} \ln \left[ \frac{\frac{(1+\phi_T)}{\beta_T} f_T \left( w_i \frac{(1+\phi_T)}{\beta_T} - \frac{(1-\beta_T)}{\beta_T} \frac{(1+\phi_T)}{(1-\tau_T)} rU \right)}{1 - F_T(x_T^*)} \right] + \sum_{i \in N_T} \ln e_T \\ &\quad + \sum_{i \in N_P} \ln \left[ \frac{\exp(-\lambda_P t_{i,e_P}) \frac{(1+\phi_P)}{\beta_P} f_P \left( w_i \frac{(1+\phi_P)}{\beta_P} - \frac{(1-\beta_P)}{\beta_P} \frac{(1+\phi_P)}{(1-\tau_P)} rU + \lambda_P \Psi \right)}{1 - F_P(x_{OP}^*)} \right. \\ &\quad \left. + \frac{(1 - \exp(-\lambda_P t_{i,e_P})) \frac{(1+\phi_P)}{\beta_P} f_P \left( w_i \frac{(1+\phi_P)}{\beta_P} - \frac{(1-\beta_P)}{\beta_P} \frac{(1+\phi_P)}{(1-\tau_P)} rU - r\Psi \right)}{1 - F_P(x_{IP}^*)} \right] \\ &\quad + \sum_{i \in N_P} \ln e_P \tag{A4.1} \end{aligned}$$

Considering first the contribution of unemployment duration, the unemployment rate, and the employment rates in jobs with both types of contracts in equation (A4.1):

$$N_{u,P} h_u^P - h_u^P \sum_{i \in N_{u,P}} t_{u,i} + N_{u,T} h_u^T - h_u^T \sum_{i \in N_{u,T}} t_{u,i} + N_u \ln u + N_T \ln e_T + N_P \ln e_P$$

The steady-state equilibrium conditions, equations (2.10) to (2.12), can be written in terms of the hazard rates out of unemployment and out of employment in the following way:

$$u = \frac{h_E^T h_E^P}{h_u^P h_E^T + h_u^T h_E^P + h_E^T h_E^P}, \quad e_P = \frac{h_u^P h_E^T}{h_u^P h_E^T + h_u^T h_E^P + h_E^T h_E^P}, \quad e_T = \frac{h_u^T h_E^P}{h_u^P h_E^T + h_u^T h_E^P + h_E^T h_E^P}$$

where:

$$h_u^P = \alpha_w^P [1 - F_P(x_{OP}^*)], \quad h_u^T = \alpha_w^T [1 - F_T(x_T^*)], \quad h_E^P = \lambda_P F_P(x_{IP}^*), \quad h_E^T = \lambda_T$$

Replacing these equations, the following is obtained:

$$N_{u,P} h_u^P - h_u^P \sum_{i \in N_{u,P}} t_{u,i} + N_{u,T} h_u^T - h_u^T \sum_{i \in N_{u,T}} t_{u,i} + (N_u + N_T) \ln h_E^P + (N_u + N_P) h_E^T \\ N_T \ln h_u^T + N_P \ln h_u^P + N \ln (h_u^P h_E^T + h_u^T h_E^P + h_E^T h_E^P)$$

Now, taking the first order conditions with respect to the hazard rates:

$$\begin{aligned} h_u^P : \quad N_{u,P} - \sum_{i \in N_{u,P}} t_{u,i} + N_P \frac{1}{h_u^P} + N \frac{1}{h_u^P h_E^T + h_u^T h_E^P + h_E^T h_E^P} h_E^T &= 0 \\ h_u^T : \quad N_{u,T} - \sum_{i \in N_{u,T}} t_{u,i} + N_T \frac{1}{h_u^T} + N \frac{1}{h_u^P h_E^T + h_u^T h_E^P + h_E^T h_E^P} h_E^P &= 0 \\ h_E^P : \quad (N_u + N_T) \frac{1}{h_E^P} + N \frac{1}{h_u^P h_E^T + h_u^T h_E^P + h_E^T h_E^P} (h_u^T + h_E^T) &= 0 \\ h_E^T : \quad (N_u + N_P) \frac{1}{h_E^T} + N \frac{1}{h_u^P h_E^T + h_u^T h_E^P + h_E^T h_E^P} (h_u^P + h_E^P) &= 0 \end{aligned}$$

The system can be solved for the four unknowns. So the hazard rates out of unemployment and out of employment are identified just with unemployment duration data and the transitions from unemployment to both types of contracts. In terms of the

model parameters:

$$h_u^P = \alpha_w^P [1 - F_P(x_{OP}^*)] \quad (\text{A4.2})$$

$$h_u^T = \alpha_w^T [1 - F_T(x_T^*)] \quad (\text{A4.3})$$

$$h_E^P = \lambda_P F_P(x_{IP}^*) \quad (\text{A4.4})$$

$$h_E^T = \lambda_T \quad (\text{A4.5})$$

On the other hand, recalling from equation (A4.1), the contribution to the likelihood of wage of temporary workers was:

$$\sum_{i \in N_T} \ln \left[ \frac{\frac{(1+\phi_T)}{\beta_T} f_T \left( w_i \frac{(1+\phi_T)}{\beta_T} - \frac{(1-\beta_T)}{\beta_T} \frac{(1+\phi_T)}{(1-\tau_T)} rU \right)}{1 - F_T(x_T^*)} \right]$$

Now, using location and scale parameters notation:

$$\sum_{i \in N_T} \ln \left[ \frac{\frac{1}{S_T} f_T \left( \frac{w_i - L_T}{S_T} \right)}{1 - F_T(x_T^*)} \right]$$

where:

$$L_T = \frac{(1 - \beta_T)}{(1 - \tau_T)} rU + \frac{\beta_T}{(1 + \phi_T)} \mu_T^x \quad (\text{A4.6})$$

$$S_T = \frac{\beta_T}{(1 + \phi_T)} \sigma_T^x \quad (\text{A4.7})$$

Note that  $L_T$  and  $S_T$  are identified from temporary jobs wage data. Finally, the wage contribution to the likelihood of workers with permanent contracts in equation (A4.1) was:

$$\sum_{i \in N_P} \ln \left[ \frac{\exp(-\lambda_P t_{i,e_P}) \frac{(1+\phi_P)}{\beta_P} f_P \left( w_i \frac{(1+\phi_P)}{\beta_P} - \frac{(1-\beta_P)}{\beta_P} \frac{(1+\phi_P)}{(1-\tau_P)} rU + \lambda_P \Psi \right)}{1 - F_P(x_{OP}^*)} \right. \\ \left. + \frac{(1 - \exp(-\lambda_P t_{i,e_P})) \frac{(1+\phi_P)}{\beta_P} f_P \left( w_i \frac{(1+\phi_P)}{\beta_P} - \frac{(1-\beta_P)}{\beta_P} \frac{(1+\phi_P)}{(1-\tau_P)} rU - r\Psi \right)}{1 - F_P(x_{IP}^*)} \right]$$

Now, using the location and scale parameters notation again, the following is obtained:

$$\sum_{i \in N_P} \ln \left[ \frac{\exp(-\lambda_P t_{i,e_P}) \frac{1}{S_{OP}} f_P \left( \frac{w_i - L_{OP}}{S_{OP}} \right)}{1 - F_P(x_{OP}^*)} + \frac{(1 - \exp(-\lambda_P t_{i,e_P})) \frac{1}{S_{IP}} f_P \left( \frac{w_i - L_{IP}}{S_{IP}} \right)}{1 - F_P(x_{IP}^*)} \right]$$

where:

$$L_{OP} = \frac{(1 - \beta_P)}{(1 - \tau_P)} rU + \lambda_P \Psi + \frac{\beta_P}{(1 + \phi_P)} \mu_P^x \quad (\text{A4.8})$$

$$L_{IP} = \frac{(1 - \beta_P)}{(1 - \tau_P)} rU - r\Psi + \frac{\beta_P}{(1 + \phi_P)} \mu_P^x \quad (\text{A4.9})$$

$$S_{OP} = S_{IP} = S_P = \frac{\beta_P}{(1 + \phi_P)} \sigma_P^x \quad (\text{A4.10})$$

The contribution of permanent job wages is a mixture of two truncated normal distributions that share the same scale parameter. Because the weights change in a deterministic way, Teicher (1963) result apply so  $L_{OP}, L_{IP}, S_P, \lambda_P$  are identified from wage data. Finally, the model restrictions are:

$$x_{IP}^* = \frac{(1 + \phi_P)}{(1 - \tau_P)} rU - r\Psi - \frac{\lambda_P}{r + \lambda_P} \int_{x_{IP}^*}^{\infty} (x' - x_{IP}^*) f_P(x') dx' \quad (\text{A4.11})$$

$$x_{OP}^* = x_{IP}^* + (\lambda_P + r) \Psi \quad (\text{A4.12})$$

$$x_T^* = \frac{(1 + \phi_T)}{(1 - \tau_T)} rU \quad (\text{A4.13})$$

It is possible to recover all the model parameters in the likelihood by solving equations (A4.2) to (A4.13) for twelve unknowns,  $(\alpha_w^P, \alpha_w^T, \lambda_P, \lambda_T, rU, x_{OP}^*, x_{IP}^*, x_T^*, \mu_x^P, \sigma_x^P, \mu_x^T, \sigma_x^T)$ .

## APPENDIX B

### APPENDIX TO CHAPTER 2

#### B.1 VALUE FUNCTIONS AND COMPUTATIONAL ALGORITHM

This appendix presents the full derivation of the equations of section 3.3 and discusses an algorithm to solve the dynamic programming problem. If an infinitesimally small period of time  $\Delta t$  is considered, then the value of unemployment is:

$$U = b\Delta t + \frac{1}{1 + \rho\Delta t} \left\{ \begin{array}{l} [\lambda_U \Delta t + \sigma(\Delta t)] \int \max \{U, W(w')\} dG(w') \\ + (1 - [\lambda_U \Delta t + \sigma(\Delta t)]) U \end{array} \right\}$$

Operating and dividing by  $\Delta t$ :

$$\begin{aligned} \frac{(1 + \rho\Delta t)}{\Delta t} U &= \frac{(1 + \rho\Delta t)}{\Delta t} b\Delta t + \frac{[\lambda_U \Delta t + \sigma(\Delta t)]}{\Delta t} \int \max \{U, W(w')\} dG(w') \\ &+ \left( \frac{1}{\Delta t} - \frac{[\lambda_U \Delta t + \sigma(\Delta t)]}{\Delta t} \right) U \end{aligned}$$

Note that:

$$\lim_{\Delta t \rightarrow 0} \frac{\sigma(\Delta t)}{\Delta t} = 0$$

Taking  $\Delta t \rightarrow 0$  and rearranging:

$$\rho U = b + \lambda_U \int \max \{0, W(w' - U)\} dG(w')$$

Now using the decision rule:

$$\rho U = b + \lambda_U \left( \int_{-\infty}^{w^*} 0 dG(w') + \int_{w^*}^{\infty} (W(w') - U) dG(w') \right)$$

Therefore:

$$\rho U = b + \int_{w^*}^{\infty} (W(w') - U) dG(w')$$

The value of employment, on the other hand, can be written as:

$$W(w) = w\Delta t + \frac{1}{1 + \rho\Delta t} \left\{ \begin{array}{l} [\eta\Delta t + \sigma(\Delta t)] U + [\lambda_E\Delta t + \sigma(\Delta t)] \int \max \{W(w), W(w')\} dG(w') \\ \quad + [\lambda_R\Delta t + \sigma(\Delta t)] \int \max \{U, W(w')\} dG(w') \\ \quad + (1 - [\eta\Delta t + \sigma(\Delta t)] - [\lambda_E\Delta t + \sigma(\Delta t)] - [\lambda_R\Delta t + \sigma(\Delta t)]) W(w) \end{array} \right\}$$

Operating and dividing by  $\Delta t$ :

$$\begin{aligned} \frac{(1 + \rho\Delta t)}{\Delta t} W(w) &= \frac{(1 + \rho\Delta t) w\Delta t}{\Delta t} + \frac{[\eta\Delta t + \sigma(\Delta t)]}{\Delta t} U \\ &\quad + \frac{[\lambda_E\Delta t + \sigma(\Delta t)]}{\Delta t} \int \max \{W(w), W(w')\} dG(w') \\ &\quad + \frac{[\lambda_R\Delta t + \sigma(\Delta t)]}{\Delta t} \int \max \{U, W(w')\} dG(w') \\ &\quad + \left( \frac{1}{\Delta t} - \frac{[\eta\Delta t + \sigma(\Delta t)]}{\Delta t} - \frac{[\lambda_E\Delta t + \sigma(\Delta t)]}{\Delta t} - \frac{[\lambda_R\Delta t + \sigma(\Delta t)]}{\Delta t} \right) W(w) \end{aligned}$$

Taking one more time  $\Delta t \rightarrow 0$  and rearranging:

$$\begin{aligned} \rho W(w) &= w + \eta(U - W(w)) + \lambda_E \int \max \{0, W(w') - W(w)\} dG(w') \\ &\quad + \lambda_R \int \max \{U - W(w), W(w') - W(w)\} dG(w') \end{aligned}$$

Using the decision rule one more time:

$$\begin{aligned} \rho W(w) &= w + \eta(U - W(w)) + \lambda_E \left( \int_{-\infty}^w 0 dG(w') + \int_w^{\infty} (W(w') - W(w)) dG(w') \right) \\ &\quad + \lambda_R \left( \int_{-\infty}^{w^*} (U - W(w)) dG(w') + \int_{w^*}^{\infty} (W(w') - W(w)) dG(w') \right) \end{aligned}$$

Note that:

$$\int_{-\infty}^{w^*} (U - W(w)) dG(w') = (U - W(w)) \int_{-\infty}^{w^*} dG(w') = (U - W(w)) G(w^*)$$

Therefore:

$$\begin{aligned}\rho W(w) &= w + (\eta + \lambda_R G(w^*))(U - W(w)) + \lambda_E \int_w^\infty (W(w') - W(w))dG(w') \\ &\quad + \lambda_R \int_{w^*}^\infty (W(w') - W(w))dG(w')\end{aligned}$$

It is known that  $W(w^*) = U$  and  $W(w) = W(w')$  hold for the reservation wages (in the unemployment state and in the on the job search case, respectively). Using the value of unemployment it is possible to write:

$$U = \frac{b}{(\rho + \lambda_U \tilde{G}(w^*))} + \frac{\lambda_U}{(\rho + \lambda_U \tilde{G}(w^*))} \int_{w^*}^\infty W(w')dG(w')$$

Using the value of employment and evaluating in  $w^*$ :

$$\begin{aligned}w^* &= (\rho + \eta + \lambda_R + \lambda_E \tilde{G}(w^*)) W(w^*) - [\eta + \lambda_R G(w^*)] U - \lambda_E \int_{w^*}^\infty W(w')dG(w') \\ &\quad - \lambda_R \int_{w^*}^\infty W(w')dG(w')\end{aligned}$$

Now given  $W(w^*) = U$ :

$$w^* = (\rho + (\lambda_E + \lambda_R) \tilde{G}(w^*)) U - (\lambda_E + \lambda_R) \int_{w^*}^\infty W(w')dG(w')$$

Replacing  $U$  in the last equation:

$$w^* = \frac{(\rho + (\lambda_E + \lambda_R) \tilde{G}(w^*))}{(\rho + \lambda_U \tilde{G}(w^*))} \left[ b + \lambda_U \int_{w^*}^\infty W(w')dG(w') \right] - (\lambda_E + \lambda_R) \int_{w^*}^\infty W(w')dG(w')$$

Naming  $\gamma(w^*) = \frac{(\rho + (\lambda_E + \lambda_R) \tilde{G}(w^*))}{(\rho + \lambda_U \tilde{G}(w^*))}$  then:

$$w^* = \gamma(w^*) \left[ b + \lambda_U \int_{w^*}^\infty W(w')dG(w') \right] - (\lambda_E + \lambda_R) \int_{w^*}^\infty W(w')dG(w')$$

or alternatively:

$$w^* = \gamma(w^*)b + [\gamma(w^*)\lambda_U - \lambda_E - \lambda_R] \int_{w^*}^\infty W(w')dG(w')$$



Now using the value of employment, the fact that  $U = W(w^*)$  and calling  $\theta(w) = \frac{1}{(\rho + \eta + \lambda_R + \lambda_E \tilde{G}(w))}$ :

$$W(w) = \theta(w) \left\{ \begin{array}{l} w + [\eta + \lambda_R G(w^*)] W(w^*) \\ + \lambda_E \int_w^\infty W(w') dG(w') + \lambda_R \int_{w^*}^\infty W(w') dG(w') \end{array} \right\}$$

### Algorithm to Solve the Fixed Point

1. Construct a grid in  $w \in [0, \bar{w}]$ . Guess  $W_0(w)$  (for all values of  $w$  in the grid) and  $w_0^*$ .
2. Given  $W_n(w)$  and  $w_n^*$  calculate  $W_{n+1}(w)$  and  $w_{n+1}^*$  using:

$$w_{n+1}^* = \gamma(w_n^*)b + [\gamma(w_n^*)\lambda_U - \lambda_E - \lambda_R] \int_{w_n^*}^\infty W_n(w') dG(w')$$

$$W_{n+1}(w) = \theta(w) \left\{ \begin{array}{l} w + [\eta + \lambda_R G(w_n^*)] W_n(w_n^*) \\ + \lambda_E \int_w^\infty W_n(w') dG(w') + \lambda_R \int_{w_n^*}^\infty W_n(w') dG(w') \end{array} \right\}$$

3. If  $|W_{n+1}(w) - W_n(w)| < \varepsilon$  and  $|w_{n+1}^* - w_n^*| < \varepsilon$ , then stop the iteration and the solution is  $W_{n+1}(w)$  and  $w_{n+1}^*$ . Otherwise return to 2 with the following updated:

$$W_{new}(w) = W_n(w) + \lambda (W_{n+1}(w) - W_n(w))$$

$$w_{new}^* = w_n^* + \lambda (w_{n+1}^* - w_n^*)$$



## B.2 THE LIKELIHOOD FUNCTION

$$\begin{aligned}
L(X=1) &= \{f_u(t_u, c_u = 1)\}^{c_u} \left\{ f_u(t_u) \int_{w_u^*} f_e(t_1, c_1 = 1|w_u) \frac{1}{w_u} q\left(\frac{w_u}{w_u}\right) f_w(w_u) dw_u \right\}^{(1-c_u)c_1} \\
&\times \left\{ f_u(t_u) \int_{w_u^*} f_e(t_1, r_1 = 1|w_u) \frac{1}{w_u} q\left(\frac{w_u}{w_u}\right) f_w(w_u) dw_u \right\}^{(1-c_u)(1-c_1)r_1} \\
&\times \left\{ \phi(w_u^0, w_2^0) \left[ \begin{aligned} &f_u(t_u) \int_{w_u^*} f_e(t_1, w_2 > w_u|w_u) \frac{1}{w_u} q\left(\frac{w_u}{w_u}\right) f_w(w_u) \\ &\int_{w_2} f_e(t_2, c_2^r = 1|w_2) \frac{1}{w_2} q\left(\frac{w_2^0}{w_2}\right) f_w(w_2, w_2 > w_u|w_u) dw_2 dw_u \end{aligned} \right] \right. \\
&\quad \left. + (1 - \phi(w_u^0, w_2^0)) \left[ \begin{aligned} &f_u(t_u) \int_{w_u^*} f_e(t_1, w_2 < w_u|w_u) \frac{1}{w_u} q\left(\frac{w_u}{w_u}\right) f_w(w_u) \\ &\int_{w_2} f_e(t_2, c_2^r = 1|w_2) \frac{1}{w_2} q\left(\frac{w_2^0}{w_2}\right) f_w(w_2, w_2 < w_u|w_u) dw_2 dw_u \end{aligned} \right] \right\}^{(1-c_u)(1-c_1)(1-r_1)c_2} \\
&\times \left\{ \phi(w_u^0, w_2^0) \left[ \begin{aligned} &f_u(t_u) \int_{w_u^*} f_e(t_1, w_2 > w_u|w_u) \frac{1}{w_u} q\left(\frac{w_u}{w_u}\right) f_w(w_u) \\ &\int_{w_2} f_e(t_2, r_2 = 1|w_2) \frac{1}{w_2} q\left(\frac{w_2^0}{w_2}\right) f_w(w_2, w_2 > w_u|w_u) dw_2 dw_u \end{aligned} \right] \right. \\
&\quad \left. + (1 - \phi(w_u^0, w_2^0)) \left[ \begin{aligned} &f_u(t_u) \int_{w_u^*} f_e(t_1, w_2 < w_u|w_u) \frac{1}{w_u} q\left(\frac{w_u}{w_u}\right) f_w(w_u) \\ &\int_{w_2} f_e(t_2, r_2 = 1|w_2) \frac{1}{w_2} q\left(\frac{w_2^0}{w_2}\right) f_w(w_2, w_2 < w_u|w_u) dw_2 dw_u \end{aligned} \right] \right\}^{(1-c_u)(1-c_1)(1-r_1)(1-c_2)r_2} \\
&\times \left\{ \phi(w_u^0, w_2^0) \left[ \begin{aligned} &f_u(t_u) \int_{w_u^*} f_e(t_1, w_2 > w_u|w_u) \frac{1}{w_u} q\left(\frac{w_u}{w_u}\right) f_w(w_u) \\ &(1 - \phi(w_2^0, w_3^0)) \int_{w_2} f_e(t_2, w_3 < w_2|w_2) \frac{1}{w_2} q\left(\frac{w_2^0}{w_2}\right) f_w(w_2, w_2 > w_u|w_u) dw_2 \\ &f_u(t_u) \int_{w_u^*} f_e(t_1, w_2 > w_u|w_u) \frac{1}{w_u} q\left(\frac{w_u}{w_u}\right) f_w(w_u) \end{aligned} \right] \right. \\
&\quad \left. + (1 - \phi(w_u^0, w_2^0)) \left[ \begin{aligned} &\phi(w_2^0, w_3^0) \int_{w_2} f_e(t_2, w_3 > w_2|w_2) \frac{1}{w_2} q\left(\frac{w_2^0}{w_2}\right) f_w(w_2, w_2 > w_u|w_u) dw_2 \\ &(1 - \phi(w_2^0, w_3^0)) \int_{w_2} f_e(t_2, w_3 < w_2|w_2) \frac{1}{w_2} q\left(\frac{w_2^0}{w_2}\right) f_w(w_2, w_2 < w_u|w_u) dw_2 \\ &f_u(t_u) \int_{w_u^*} f_e(t_1, w_2 < w_u|w_u) \frac{1}{w_u} q\left(\frac{w_u}{w_u}\right) f_w(w_u) \end{aligned} \right] \right\}^{(1-c_u)(1-c_1)(1-r_1)(1-c_2)r_2} \\
&\times \left\{ \phi(w_u^0, w_2^0) \left[ \begin{aligned} &f_u(t_u) \int_{w_u^*} f_e(t_1, w_2 > w_u|w_u) \frac{1}{w_u} q\left(\frac{w_u}{w_u}\right) f_w(w_u) \\ &\phi(w_2^0, w_3^0) \int_{w_2} f_e(t_2, w_3 > w_2|w_2) \frac{1}{w_2} q\left(\frac{w_2^0}{w_2}\right) f_w(w_2, w_2 > w_u|w_u) dw_2 \\ &(1 - \phi(w_2^0, w_3^0)) \int_{w_2} f_e(t_2, w_3 < w_2|w_2) \frac{1}{w_2} q\left(\frac{w_2^0}{w_2}\right) f_w(w_2, w_2 > w_u|w_u) dw_2 \\ &f_u(t_u) \int_{w_u^*} f_e(t_1, w_2 < w_u|w_u) \frac{1}{w_u} q\left(\frac{w_u}{w_u}\right) f_w(w_u) \end{aligned} \right] \right. \\
&\quad \left. + (1 - \phi(w_u^0, w_2^0)) \left[ \begin{aligned} &\phi(w_2^0, w_3^0) \int_{w_2} f_e(t_2, w_3 > w_2|w_2) \frac{1}{w_2} q\left(\frac{w_2^0}{w_2}\right) f_w(w_2, w_2 < w_u|w_u) dw_2 \\ &(1 - \phi(w_2^0, w_3^0)) \int_{w_2} f_e(t_2, w_3 < w_2|w_2) \frac{1}{w_2} q\left(\frac{w_2^0}{w_2}\right) f_w(w_2, w_2 < w_u|w_u) dw_2 \\ &f_u(t_u) \int_{w_u^*} f_e(t_1, w_2 < w_u|w_u) \frac{1}{w_u} q\left(\frac{w_u}{w_u}\right) f_w(w_u) \end{aligned} \right] \right\}^{(1-c_u)(1-c_1)(1-r_1)(1-c_2)r_2}
\end{aligned}$$



## APPENDIX C

### APPENDIX TO CHAPTER 3

#### C.1 DATA SOURCES AND DEFINITIONS

##### DATA USED IN THE DESCRIPTIVE EVIDENCE SECTION.

The data used in the descriptive evidence section are extracted from the Annual Social and Economics Supplement (ASES or March Supplement) and the School Enrollment Supplement (October Supplement) of the Current Population Survey (CPS). The first supplement contains data on family characteristics, household composition, marital status, education attainment, earnings, labor market status, work experience, job characteristics. The second focuses on school enrollment, college attendance, fields of study, major choices. Both supplements are conducted annually. The March yearly supplement from 1981 to 2011 and the October supplement in 2002 is used. Only the 2002 supplement is used because it is the only one reporting Field of Study choice.

##### INDIVIDUAL CHARACTERISTICS

The individual characteristics are obtained from the CPS questions on gender, race, age, marital status, and presence of kids under 18 years in the household. The year of birth, for the analysis by cohort, was inferred from the year of the survey and the age.

## EDUCATION LEVEL AND FIELDS OF STUDY

The education levels and fields of study choices are obtained from the set of questions related to education attainment in the March Supplement and with school enrollment in the October Supplement. Education level is classified in three groups according to the highest degree obtained: (1) Masters and Doctorate degree, (2) College degree and (3) High School degree. It is important to mention that this classification is used from 1992 onward, because in that year there was a major change in the coding of the CPS data to classify education attainment. For the survey years before 1992, college graduates are simply defined as persons with 14 or more years of education.

The gap in Figures 4.1 and 4.2 is calculated as a percentage difference with respect to men, that is  $\frac{(x_W - x_M)}{x_M}$  where  $x$  is the percentage of college graduates.

The Field of Choice variable is only collected in the October supplement of 2002 and this is why Figures 4.4 and 4.5 report the distribution only on 2002.

## LABOR MARKET STATUS

The labor market status (employment, unemployment and non-participation) is obtained by a set of questions organized by the CPS team in the monthly labor force recode variable which directly assigns each individual in the sample to employment, unemployment or not-in-the labor force status. Excluded from the universe are kids and individuals in the armed forces.

## EARNINGS AND HOURS WORKED

Hourly earnings are obtained either by using the value directly reported in the CPS survey or by computing the value dividing weekly earnings by the usual hours worked per week. Earnings are measured in real terms. Earnings are expressed in 2005 US

dollars by deflating them by the Consumer Price Index for All Urban Consumers. For hours worked, as before, the usual hours worked per week directly reported in the survey is used.

#### UNEMPLOYMENT DURATIONS

Unemployment durations are measured in months and they are obtained by rescaling the original weekly unemployment durations reported in the CPS.

#### JOB CHARACTERISTICS

The job characteristics are obtained from the set of questions related to full/part time jobs and occupational classification. The codes in this last variable are the 2002 NAICS equivalent. It is important to mention that all the descriptive analysis related with occupations is done from 2002 onward because in that year there was a major change in the coding used in the CPS to classify occupations.

#### DATA USED IN THE IMPACT OF EMPLOYER'S PREJUDICE SECTION

The data used in the structural estimation of the search-matching-bargaining model with employers taste discrimination are extracted from the March Supplement of the CPS for 1995 and 2005. These years were chosen because they satisfy two criteria. First, these are neither boom nor recession years, and therefore they seem appropriate to describe a model under the steady state assumption. Second, they are equally spaced over-time and far away enough to potentially describe different steady-states.

An important assumption in the model is ex-ante agents' homogeneity. To obtain the estimation sample, individuals homogeneous sample with respect to the following characteristics: race (white), age (30 to 55 years old) and education (MA and PhD; College; High School) are extracted.

The variables used in the estimation are: real hourly wages, unemployment duration in months, gender, education level, and labor market status. Wages are available only for individuals currently employed, and unemployed duration only for individuals currently unemployed. As a result unemployment durations are not complete spells but on-going spells.

Table 4.1 presents the number of observations and descriptive statistics, by education level and year, of the sample used in the Maximum Likelihood Estimation procedure.



## C.2 THE LIKELIHOOD FUNCTION

The reservation wages are estimated as:

$$\hat{w}_{gye}^* = \min_{w_i} \{w_i, i \in E_{gye}\}$$

Duration data contribution to the likelihood function, conditional on gender, year and education level, is:

$$\begin{aligned} f_u(t_i, i \in U|g, y, e) &= f_u(t_i|i \in U, g, y, e)P(i \in U|g, y, e) \\ &= h_{gye} \exp(-h_{gye}t_i) \frac{\eta_{gye}}{\eta_{gye} + h_{gye}}, \quad t_i > 0 \end{aligned}$$

where

$$h_{gye} = \lambda_{gye} [(1 - p_{ye})(1 - G_{gye}(w_{gye}^*)) + p_{ye}(1 - G_{gye}(w_{gye}^* + d_{ye}\mathbf{I}_{(g=W)}))]$$

On the other hand, wages data contribution to the likelihood function, conditional on gender, year and education level, is:

$$\begin{aligned} f_e(w_i, w_i > w_i^*, i \in E|g, y, e) &= f_e(w_i|i \in E, g, y, e)P(w_i > w_i^*|i \in E, g, y, e)P(i \in E|g, y, e) \\ &= \left[ \frac{\frac{1-p_{ye}}{\alpha} g_{gye} \left( \frac{w_i - (1-\alpha)w_{gye}^*}{\alpha} \right)}{1 - G_{gye}(w_{gye}^*)} + \frac{\frac{p_{ye}}{\alpha} g_{gye} \left( \frac{w_i + \alpha d_{ye}\mathbf{I}_{(g=W)} - (1-\alpha)w_{gye}^*}{\alpha} \right)}{1 - G_{gye}(w_{gye}^* + d_{ye}\mathbf{I}_{(g=W)})} \right] \frac{h_{gye}}{\eta_{gye} + h_{gye}} \end{aligned}$$

Wages contribution is defined for  $w_i > w_{gye}^*$ . See Flabbi [2010a] for a detailed explanation of the derivations of the above contributions. The concentrated likelihood

function, conditional on education level, can be written as:

$$\begin{aligned}
L(\Omega; t, w|e) &= \prod_{i=1}^N \left\{ \left[ \begin{array}{l} (f_u(t_i, i \in U|M, 95, e))^{\mathbf{I}(i \in U_{M95e})} \\ (f_e(w_i, w_i > w_i^*, i \in E|M, 95, e))^{1-\mathbf{I}(i \in U_{M95e})} \end{array} \right]^{\mathbf{I}(g=M)} \right. \\
&\quad \times \left. \left[ \begin{array}{l} (f_u(t_i, i \in U|W, 95, e))^{\mathbf{I}(i \in U_{W95e})} \\ (f_e(w_i, w_i > w_i^*, i \in E|W, 95, e))^{1-\mathbf{I}(i \in U_{W95e})} \end{array} \right]^{1-\mathbf{I}(g=M)} \right\}^{\mathbf{I}(y=95)} \\
&\quad \times \left\{ \left[ \begin{array}{l} (f_u(t_i, i \in U|M, 05, e))^{\mathbf{I}(i \in U_{M05e})} \\ (f_e(w_i, w_i > w_i^*, i \in E|M, 05, e))^{1-\mathbf{I}(i \in U_{M05e})} \end{array} \right]^{\mathbf{I}(g=M)} \right. \\
&\quad \times \left. \left[ \begin{array}{l} (f_u(t_i, i \in U|W, 05, e))^{\mathbf{I}(i \in U_{W05e})} \\ (f_e(w_i, w_i > w_i^*, i \in E|W, 05, e))^{1-\mathbf{I}(i \in U_{W05e})} \end{array} \right]^{1-\mathbf{I}(g=M)} \right\}^{\mathbf{I}(y=05)}
\end{aligned}$$

The parameters were estimated separately by education level ( $e$ ), that is for High School, College Graduates and Master and PhD Graduates. Finally, the restriction imposed in the estimation across years was  $k_{95e} = k_{05e}$ , where  $k_{ye} = \frac{d_{ye}}{E[x|M, y, e]}$ .

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