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Labor Market Structure and Welfare: A Comparison of Italy and the U.S.*

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Abstract

Characteristics of cross-sectional earnings distributions are often used to compare the equity of various labor market structures. We demonstrate the labor markets in which cross-sectional earnings dispersion is large [as measured by the coefficient of variation, for example] may produce low levels of variation in lifetime welfare outcomes. We use an on-the-job search framework and individual-level event history data from Italy and the U.S. to show that Italian labor market institutions produce lower levels of cross-sectional inequality in hourly wage rates and monthly earnings, but imply higher levels of lifetime welfare inequality in hourly wage rates and only slightly lower inequality in monthly earnings than do U.S. institutions.

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1 Introduction

Institutional environments are often compared in terms of the distribution of welfare outcomes they "produce." A popular theme is the comparison of inequality across countries. Typically measures of dispersion such as the coefficient of variation or Gini index are computed using cross-sectional earnings or income distributions for purposes of comparing degrees of inequality across countries.[1] In this research we make the point that the comparison of inequality measures computed from cross-sectional distributions may lead to very inaccurate assessments regarding differences in lifetime welfare inequality. We illustrate this point using individual level event history data from Italy and the U.S. and a model of off- and on-the-job search. We have chosen Italy and the U.S. to make our substantive points because the labor market institutions in these two countries are well-known to be quite dissimilar.

There exist a number of studies which compare the labor markets of Italy and the U.S., both in terms of institutional differences and empirically [see, for example, Grubb et al (1983), Del Boca (1988), Bertola and Ichino (1995a,1995b), Blanchflower et al (1993), Demekas (1994)]. In virtually all of the empirical studies, differences in the industrial relations systems and/or output markets are invoked to explain patterns of intertemporal relationships between comparable [typically aggregated] labor market measures in the two countries. A popular focus of this type of analysis is on the effect of the severe restrictions on layoffs in Italy on the responsiveness of employment to business cycle shocks in comparison with cyclical variability in employment in the U.S.

While the Italian labor market has generally become less regulated over the past few decades, it remains to this day substantially more regulated than the U.S. market. Some researchers have claimed that recent changes in the industrial relations system in Italy and competitive pressures in product markets have made the Italian market very similar to the U.S. market in terms of layoff and hiring rates [e.g., Bertola and Ichino (1995b)]. These claims have been made on the basis of empirical work typically done at the industry [or more aggregated] level. One reason for this state of affairs is that there exists no nationally representative data base in Italy which can be used to assess movements across labor market states [including switches in firms] at the individual level. In this paper I make comparisons of labor market dynamics across the two countries by exploiting ret-

[1]For example, in an intertemporal analysis of inequality of earnings in Italy, Brandolini and Sestito (1994,1996) compare coefficients of variation from year-specific earnings distributions [as well as other inequality measures]. Of substantive interest to this study is their finding that "inequality" in Italian earnings was relatively low in the period spanned by our data, 1988-89. We should note that while we will criticize the use of cross-sectional remuneration distributions for assessing "true" welfare inequality, the stationary search model used in our analysis implies that remuneration distributions should be constant over time, which is not consistent with their empirical findings.

rospective information collected from a sample of individuals from the Lombardia region of Italy [which includes Milan] and data on the labor market experiences of white males of the same ages from the representative portion of the National Longitudinal Survey of Youth [NLSY]. To my knowledge, this is the first study to compare the two labor markets by estimating structural search models using individual-level event history data.

While we will not attempt to give a detailed account of the Italian industrial relations system we will provide a brief overview of some of its more important features. Consider first hiring. Italy was until recently the only European country to attempt to regulate precisely whom an employer could hire through the distribution of lists with candidates ranked in terms of criteria which mainly relate to their "need" for employment [i.e., whether they have dependents, whether they are the head of household or not, whether they have a disability, etc.]. While this system was abolished in 1991, it was still partially in effect during the period covered by our sample.

It remains notoriously difficult to fire or lay off individuals or groups of individuals within the Italian system. In order to permanently dismiss someone a quasi-legal process must be followed with evidence of serious misbehavior on the part of employees available for substantiation; if the employer is judged to have brought a false case against an employee punishments are severe. It is even difficult for an employer to lay off individuals or groups of individuals because of redundancy; in such a case employers are required to consult with union representatives or the government in an attempt to lessen the negative impact of separations on employees. Once again, individuals or groups of employees can contest layoffs and the firm faces severe punishments if it is found to have misrepresented its case for layoffs.

Italian firms also face severe restrictions with respect to the way in which they can utilize their work force. Despite the relaxation of some regulations pertaining to the work intensity margin in the 1980s, it is difficult for Italian firms to hire workers under fixed-term contracts and to restrict hours [the share of part-time to total employment in Italy is the lowest in Europe].

The wage-setting process, while having been liberalized in the last decade, still remains highly centralized in comparison with the U.S. "Baseline" agreements are negotiated at national and regional levels between employer organizations and the major trade unions. During the 1980s, firm-level bargaining with individual unions became increasingly important and as a result wage differentials between various classes of workers have been widening. The change which occurred during the 1980s came about due to shifts in the bargaining power of employers and unions rather than due to changes in regulatory laws *per se.* The wage determination system was formally changed in new laws introduced in 1992-93.

Because of the variation in labor market regulations across states in the U.S., it is not possible to give an analogous overview of the U.S. regulatory environment, but such an exercise is really not required for our purposes. It is clear that the Italian system is much more regulated than what is found in any locality in the U.S. on virtually every dimension.

In the context of a model of labor market dynamics estimated using individual-level data from the two countries, what do the differences in the labor market structures lead us to expect? Perhaps most obvious is the implication that dismissal rates will be higher in the U.S. While in the U.S. employees, especially union members, do have recourse to procedures to contest firings or layoffs, these procedures seem almost inconsequential compared to those in place in Italy.

Due to the extreme difficulty of dismissing or modifying the employment conditions of employees, it is reasonable to expect that the rate of receiving offers would be lower in Italy than in the U.S., other things equal. This supposition is supported by the macro time series evidence and by descriptive evidence at the micro level on the duration of unemployment spells and tenure at one's current employer. Thus we expect to find the rate of receiving offers both in the unemployed and the employed states to be lower in Italy.

Because of the centralized wage-setting process and the restrictions on varying employment intensity in Italy, it is natural to expect [and indeed is consistent with conventional wisdom] that both wage and earnings distributions would be more "concentrated" in Italy than in the U.S. Figure 1 provides some evidence on this issue. It contains histograms for wages and monthly earnings of young white male U.S. employees from the NLSY who were employed in January 1988 and the wages and earnings from a same-age group from Lombardia employed in this same month. The U.S. wage and earnings distributions appear to be more right-skewed than the comparable distributions for Italy.[2] In terms of the coefficient of variation [cv] associated with the distributions, the cv for the U.S. wage distribution is almost twice as large as the Italian cv and the cv of the U.S. monthly earnings distribution is over twice as large as the Italian cv. Observations like these have led observers to claim that the regulatory system in Italy, while undoubtedly being inefficient, has led to an equalization of labor market outcomes across individuals which is socially beneficial. This is contrasted with "unregulated" markets like that of the U.S., which while more efficient come at the cost of large disparities in welfare outcomes. Using a stationary search model, we shall show that this characterization of the welfare distributions in the two countries is, at best, questionable. Indeed, we provide some evidence that participants in the U.S. labor market exhibit less dispersion in lifetime welfare levels than do participants in the Italian market.[3] Thus in this case the regulated market is associated both with inefficiency and inequality.

[2]This is true even though two extremely high wage observations were deleted from the U.S. sub-sample we extracted. Based on the demographic characteristics of the individuals involved, we decided that the wage draws were "unbelievably" high.

[3]This is true when comparing hourly wage distributions but is not the case when the remuneration measure is monthly earnings.

The plan of the paper is as follows. In Section 2 we describe the data sources and provide descriptive evidence on labor market dynamics at the individual level in the two markets. Section 3 contains the development of a stationary model of unemployed and on-the-job search which forms the basis of the structural estimation and simulation exercises which follow. Section 4 derives the link between the dynamic search model and steady state income distributions. Section 5 contains a discussion of econometric issues and the maximum likelihood estimator we utilize. We present estimation and simulation results in Section 6, and end with a brief conclusion in Section 7.

2 Data Description and Descriptive Statistics

In this section we describe the data to be used in all of the empirical analysis which follows and present some descriptive statistics which illustrate the marked differences in transitions between labor market states in these two institutional environments.

2.1 Data Description

We begin by describing the event-history data for the U.S. labor market, which is taken from the random sample respondents of the National Longitudinal Survey of Youth [NLSY]. This data set is very well-known so only a brief discussion of the information we have extracted and the sample-selection criteria are required.

As we describe below, the Italian data utilized come from a random sample of households in the Lombardia region of Italy. For a large industrial and commercial area [it includes Milan, the "commercial capitol" of Italy] it contains a relatively homogeneous labor market in the demographic sense. For purposes of comparison, we have restricted the U.S. sample to include only whites in an attempt to limit the amount of sample heterogeneity in background characteristics. Furthermore, since the observation period for the Italian data covers the period January 1988 through May 1989, we have constructed a continuous labor market history from the NLSY data which covers only this period as well. Since the sample members were 14-21 years of age in the initial survey year of 1979, they are [approximately] between the ages of 23-30 during the observation period.

For this sample of white males we have constructed event histories which include information on the duration of each job held [where a "job" is defined as an employment spell spent with a particular employer] and the hourly wage rate and monthly earnings on the job; we also have information on the length of time spent in each spell of nonemployment. We do not attempt to distinguish between periods spent actively searching and those spent out of the labor force - all are simply lumped together in the category nonemployment [though to avoid redundancy we shall sometimes call this state "unemployment"]. We have excluded from our final sample all individuals who reported never actively searching for employment and who did not hold a job over the observation period. Thus everyone in the final sample is a labor market participant in the formal sense of the term at some point in the 17 month period. We have also excluded individuals who reported being enrolled in school during the observation period or who were in the military.

The Italian Statistical Institute [ISTAT] survey was conducted in Lombardia during the summer of 1989. Respondents were asked to describe their labor market experiences rather completely over the 17 month period which spanned January 1988 through May 1989. In particular, respondents reported their labor market status on a month-by-month status over this period. They were then asked to provide detailed information on up to two jobs held as a dependent worker and one job as an independent worker during this period. All duration information was given solely on a monthly basis.

Until recently, in Italy sample members of social surveys have seldom been asked for information relating to their earnings or income from other sources. Given that wage and/or earnings information is an essential requirement for estimating a structural search model, this is the only Italian survey information in existence which can be used for this purpose.[4] Respondents were asked, as in the NLSY, to report a typical level of earnings for each job occurring during the observation period. Thus the duration and remuneration information collected is quite similar in the two surveys.

The ISTAT sample is a household sample, with detailed information concerning labor market behavior collected for each member of the household over 15 years of age. For comparability with the U.S. data, we only included individuals in the final sample who were 23-30 years of age in 1988. Italians of this age have a higher probability of living with their parents then do their American counterparts. Nonetheless, we did not insist that sample members live outside of their parents' households to be included in either sample. Our belief was that this is a cultural difference which could well be picked up in our estimates of behavioral parameters, particularly with respect to the level of monetarized utility associated with occupancy of the non-employment state. A reasonable expectation might be that living with one's parents may decrease the costs of nonemployed search.

The (limited) retrospective nature of the labor market information collected in the Italian data implies that the spell first sampled, that is the one on-going in January 1988, causes a nontrivial initial conditions problem when attempting to estimate a model of on-the-job search. If an individual was not employed at that time, no presample information was collected. If an individual was currently

[4]There are some adminstrative records from the Italian social security adminstration which may possibly be used, but it is difficult to ascribe earnings to a particular job from these data. In addition, only jobs covered by social security provisions are included; for example, all public sector jobs are excluded.

employed at the beginning of the sample period [January 1988] he or she was asked the date of the beginning of that particular job spell. The individual was not asked how many jobs he had in succession before the one occupied in January 1988.

The nature of the problem can be illustrated by referring to Figure 2, which displays two hypothetical labor market histories A and B. The individual with history A exited from nonemployment into employment at time a_1. Under the assumptions of our model, he found a better job [in the sense of one paying a higher wage] at time a_2. Thus the wage associated with his employment spell in progress at the beginning of the observation period is a random draw from the distribution $F_1(w)$, which is defined as the wage distribution of individuals whose previous labor market state was nonemployment [in our search model, $F_1(w) = F(w)/\tilde{F}(w^*)$, $w \geq w^*$, where F is the population wage offer distribution, $\tilde{F}$ is the associated survivor function, and w^* is the reservation wage of nonemployed searchers]. While the data contains the individual's report of when the job spell in progress at the beginning of the observation period started [in this case a_1], the data do not contain information regarding his labor market state immediately prior to a_1.

The individual with history B experienced a large number of job-to-job transitions prior to the onset of the observation period; in fact the individual is in his fourth [and last] job of the employment spell [which covers the period from b_1 through b_5] when the observation period begins. Unconditional on the wages associated with previous jobs in this employment spell, the wage associated with the sampled job spell will be a random draw from the distribution $F_4(w)$, which is defined as the wage distribution of individuals who have had exactly three consecutive jobs in the current employment spell prior to the current job. Assuming the wage offer distribution $F(w)$ is continuously differentiable, the distribution F_4 has an associated probability density function which is given by

$$f_4(w) = \int_{w^*}^{w} \int_{w_1}^{w} \int_{w_2}^{w} \frac{f(w)}{\tilde{F}(w_3)} \frac{f(w_3)}{\tilde{F}(w_2)} \frac{f(w_2)}{\tilde{F}(w_1)} \frac{f(w_1)}{\tilde{F}(w^*)} \, dw_3 \, dw_2 \, dw_1, \ w \geq w^*. \tag{1}$$

In Section 4 we develop a useful computational algorithm for deriving the densities $f_j(w)$, $j = 2, 3, \ldots$. These densities are only slightly special cases of standard order statistic density functions.

In Figure 3 we illustrate the large differences which can exist between the wage densities associated with different job spells [the example is constructed using structural parameter estimates from the U.S. sample]. In this example the population p.d.f. of wage offers is assumed to be Pareto with a lower bound on the support equal to the reservation wage. For the Pareto case the densities f_j have a particularly simple closed form solution

$$f_j(w) = f(w) \frac{[\alpha(\ln(w) - \ln(w^*))]^{j-1}}{j-1} ; \ w > w^*, \ j = 2, 3, \ldots . \tag{2}$$

Figure 3 contains plots of the p.d.f.s associated with the first four job spells in any given employment spell.[5] There obviously exist large differences in the shapes of these densities.

From this discussion it is apparent that in a stationary environment employment spells sampled at an arbitrarily-selected point in time will have an associated probability density function of wages which can be represented as a mixture of order statistic-type densities. Thus the steady state p.d.f. of wages is of the form

$$f^S(w) = \sum_{i=1}^{\infty} q_i f_i(w), \; w \geq w^*, \tag{3}$$

$$\sum_{i=1}^{\infty} q_i = 1, \; q_i \geq 0, \; i = 1, 2, \ldots \; . \tag{4}$$

The weight q_i corresponds to the probability that a randomly-sampled employment spell will be sampled while the i^{th} job is in progress. These weights are in general a function of all the structural parameters of the search model and can be derived in a somewhat laborious fashion; this is done in Section 4. For now, we simply illustrate the significant differences that can arise between the population wage offer density and the cross-sectional wage density. Figure 4 contains a plot of these two densities, constructed from structural parameter estimates using U.S. hourly wage data. As is clear, the cross-sectional distribution of wages stochastically dominates the population wage offer distribution. Both the mean and standard deviation are higher in the cross-sectional distribution, and in this case the coefficient of variation is markedly higher as well. Thus *ex ante* inequality in the wage offer distribution may be substantially less than the inequality observed in the cross-sectional wage distribution We will return to a discussion of this issue below.

Due to the relatively complete labor market history available in the NLSY, it is possible to avoid this particular initial conditions problem because the job spell can be computed from the history. However, for purposes of comparability we treat the two samples symmetrically and hence ignore the job number information potentially available in the NLSY. Thus the same conditional maximum likelihood [m.l.] estimator is employed for the two labor markets when estimating the structural search model.

2.2 Descriptive Statistics

We begin by looking at some descriptive statistics for our samples of U.S. and Italian labor market participants, which are reported in Table 1. First note that there are approximately four times as many individuals in the U.S. sample. In terms of numbers of spells, the discrepancy is even larger since as we shall see

[5]Since the lower bound of the support is assumed equal to the reservation wage, the population p.d.f. and f_1 are the same.

transitions between labor market states are much more frequent in the U.S. than in Italy.

Nonemployment experiences were much more common in the U.S. than in Italy. In Italy, 15 percent of the sample experienced some nonemployment during the period as opposed to 28 percent in the U.S. However, less than 1 percent of the U.S. sample remained unemployed for the entire 17 month period, as opposed to 3.5 percent of the Italian sample. Job changes were much more common in the U.S. than in Italy; 82 percent of the total Italian sample worked at the same job in all 17 months while only 56 percent of the U.S. sample did not change job over the observation period. Only 4 percent of the Italians had two or more employment spells as opposed to 35 percent of the Americans. These figures highlight the very large differences in labor market transition rates between the two countries. The difference in job-changing rates is particularly striking and will be reflected in the structural parameter estimates and simulation results presented below.

Under the assumptions upon which the search model we estimate is built, in the absence of measurement error in wage rates [or monthly earnings, if that is the remuneration measure used], all job-to-job changes [with no intervening spell of nonemployment] should be accompanied by an increase in the rate of remuneration. We note that in the Italian sample, of the 16 individuals with two or more job spells, 12 had consecutive jobs. Of these 12, 11 had higher hourly wage rates in the second job than in the first. In the U.S. sample, of the 389 individuals with consecutive jobs, 66 percent had higher wages in the second job than in the first. Thus in both samples, the tendency to have higher wages in the second job is clearly present, though especially in the U.S. sample, it is far from always the case. As we discuss below, it is necessary to add measurement error to remuneration measures to account for the discrepancy between the implications of the search model and the data.

3 The Stationary Model of Off- and On-the-Job Search

The basic model utilized throughout the analysis is structured as follows. Assume that agents are infinitely-lived, and that at each moment in time they occupy one of the following labor market states. They may be nonemployed and searching for work, a state denoted by n, or they may be employed in a job which pays a wage w - this state will be denoted $e(w)$. Job offers arrive to nonemployed individuals according to a Poisson process with parameter λ_n, and to employed individuals according to a Poisson process with parameter λ_e. For both employed and nonemployed searchers the value of the offer made is independent of the arrival process. Employment spells terminate either because (1) an employed searcher locates a better job or (2) an exogenous separation occurs. Exogenous separations arrive according to a Poisson process with parameter η; note that the rate of "involuntary" separations is assumed to be independent of the wage paid on the job. The instantaneous rate of discount is ρ. Nonemployed searchers receive an instantaneous net benefit of b which is of unrestricted sign. The wage offer distribution is given by F; the successive offers received by an individual are taken to be independently and identically distributed [i.i.d.] draws from F.

Consider an infinitesimally small period of time $\triangle t$. An agent who is currently employed at the instantaneous wage rate w may find himself in one of three states at the "end" of interval $\triangle t$. First, nothing may happen during the interval so that the individual remains employed at wage w. Second, the agent may be exogenously separated from his or her job and thus enter state n with associated value V_n. Finally, the agent may receive a new job offer with associated wage rate w'. Since the wage is the only characteristic of the job valued by the individual and there are no fixed costs associated with job-changing, the individual will change jobs if iff $w' > w$, in which case the end of "period" value will be $V_e(w')$; if $w' \leq w$ the agent will remain with his current employer and retain the match value $V_e(w)$. Thus we have the value of employment over the interval $\triangle t$ is given by

$$\begin{aligned} V_e(w) &= \frac{w\triangle t}{1+\rho\triangle t} + \frac{1}{1+\rho\triangle t}\{\eta\triangle t V_n + (1-\eta\triangle t - \lambda_e\triangle t)V_e(w) \\ &\quad +\lambda_e\triangle t\int \max[V_e(w), V_e(x)]dF(x)\} + o(\triangle t), \end{aligned} \tag{5}$$

where the term $(1+\rho\triangle t)^{-1}$ is the "infinitesimal" discount factor associated with interval $\triangle t$, $\eta\triangle t$ is the approximate probability of being terminated from one's current job at the end of the interval $\triangle t$, $(1 - \eta\triangle t - \lambda_e\triangle t)$ is the approximate probability of not being terminated or receiving a new job offer, $\lambda_e\triangle t$ is the approximate probability of receiving a new job offer, V_n is the value of the nonemployment state, and $o(\triangle t)$ is a term which has the property that $\lim_{\triangle t\to 0} o(\triangle t)/\triangle t = 0$. After collecting terms and taking the limit of [5] as $\triangle t \to 0$, we have

$$V_e(w) = \frac{w + \eta V_n + \lambda_e \int_w V_e(w')dF(w')}{\rho + \eta + \lambda_e\tilde{F}(w)}. \tag{6}$$

The value of nonemployment is similarly derived. Over a small interval $\triangle t$,

$$\begin{aligned} V_n &= \frac{b\triangle t}{1+\rho\triangle t} + \frac{1}{1+\rho\triangle t}\{\lambda_n\triangle t\int \max[V_n, V_e(w)]dF(w) \\ &\quad +(1-\lambda_n\triangle t)V_n\} + o(\triangle t) \end{aligned} \tag{7}$$

where $\lambda_n\triangle t$ is the approximate probability of receiving one job offer over the interval $\triangle t$ and $(1 - \lambda_n\triangle t)$ is the approximate probability of not receiving an offer; once again the period $\triangle t$ is taken to be sufficiently small that the probability of two or more offers is of order $o(\triangle t)$. After rearranging terms and taking limits as $\triangle t \rightarrow 0$, we have

$$V_n = \frac{b + \lambda_n \int \max[V_n, V_e(w)] dF(w)}{\rho + \lambda_n}. \tag{8}$$

Given that an offer w is received by a nonemployed individual it will be accepted if and only if $V_e(w) \geq V_n$. Note that the value of search is a constant; given the easily demonstrated result that V_e is monotone increasing in its argument, it follows that there exists a unique reservation wage w^* such that $V_e(w^*) = V_n$, where $w^* \in \mathrm{Supp}(F)$.[6] Then we can rewrite [8] as

$$V_n = \frac{b + \lambda_n \int_{w^*} V_e(w) dF(w)}{\rho + \lambda_n \tilde{F}(w^*)}. \tag{9}$$

Note that the reservation wage w^* is solely a parameter which characterizes the nonemployed searchers decision rule; it is a function of all the "primitive" parameters of the model: λ_e, λ_n, ρ, η, b, and F.

By way of summary, note that while the state valuation functions $V_e(w)$ and V_n are complicated functions of all the primitive parameters of the model, the decision rules themselves are very simply characterized as follows. If the agent is *nonemployed* and receives an offer w :

$$d_n^*(w) = \begin{cases} \text{accept offer w} & \Leftrightarrow \quad w > w^* \\ \text{continue nonemploymet} & \Leftrightarrow \quad w \leq w^* \end{cases}. \tag{10}$$

If the agent is currently employed at some wage w [greater than w^* by definition] and receives an offer w' his rule is:

$$d_{e(w)}^*(w') = \begin{cases} \text{accept new job } w' & \Leftrightarrow \quad w' > w \\ \text{continue current job } w & \Leftrightarrow \quad w' \leq w \end{cases}. \tag{11}$$

These simple rules greatly facilitate estimation of the behavioral model, as we shall see below.

4 Derivation of the Steady-State Wage Distribution

In this section we explicitly derive the mapping between the dynamic behavioral model and the steady state cross-sectional earnings distribution. Before proceeding to the details of the derivation, we present a heuristic explanation of this mapping.

[6]The notation Supp(F) denotes the support of the distribution F. Thus there exists a strictly positive probability of receiving a wage offer which will be accepted.

When individuals are sampled at some random point in time, agents who happen to be employed at the sampling time can be distinguished by the number of the job they are currently holding in the on-going employment spell. For example, in Figure 2 individual A was found in his first job in the employment spell while individual B was found to be in his fourth. The individual who has had three previous jobs in the current spell will on average have a higher wage than individual A since he has the maximum of four draws from the acceptable wage offer distribution while individual A has had only one draw.

To compute the steady state wage distribution requires us to first find the wage distribution by job order, and then to find the steady state distribution of job orders in on-going employment spells. The first task is relatively straightforward, being essentially an exercise involving order statistics. To compute the steady state job order distribution, we first compute the steady state distribution of the number of jobs in an employment spell. Conditional on there being k jobs in a completed employment spell, we then derive the probability that an individual will be sampled while in his j^{th} job, $j = 1, ..., k$. Then the probability that an individual will be found in his first job in an employment spell will be the steady state probability of having a one-job employment spell plus the conditional probability of being in the first job when sampled randomly given the employment spell ends after two jobs multiplied by the probability that the employment spell ends after two jobs, etc. We now proceed to a formal derivation of these distributions.

By the structure of the model all nonemployed individuals accept any draw from the distribution F which exceeds the reservation wage associated with the nonemployment state, w^*. Then the density of wages in the first job in an employment spell is

$$f_1(w_1) = \frac{f(w_1)}{\tilde{F}(w^*)}\, \chi[w_1 \geq w^*], \tag{12}$$

where $\chi[A]$ takes the value 1 if A is true and equals 0 if A is false.

To derive the marginal density of the wages associated with the second job in an employment spell, we first write the joint density of first and second job wages,

$$\begin{aligned} f_{1,2}(w_1, w_2) &= f_{2|1}(w_2|w_1) f_1(w_1) && (13)\\ &= \frac{f(w_2)}{\tilde{F}(w_1)}\, \chi[w_2 > w_1]\, \frac{f(w_1)}{\tilde{F}(w^*)}\, \chi[w_1 > w^*] && (14)\\ &= \frac{f(w_2)}{\tilde{F}(w^*)} \frac{f(w_1)}{\tilde{F}(w_1)}\, \chi[w_2 > w_1 > w^*], && (15) \end{aligned}$$

where the form of the conditional density $f_{2|1}$ follows from the fact that the second job is a random draw from f truncated from below at the first job wage

w_1. Integrating over w_1 to get the marginal density of w_2 we have

$$f_2(w_2) = \frac{f(w_2)}{\tilde{F}(w^*)} \left[\int_{w^*}^{w_2} h(w_1)\, dw_1\right] \chi[w_2 > w^*], \tag{16}$$

$$= \frac{f(w_2)}{\tilde{F}(w^*)} AF_2(w_2)\, \chi[w_2 > w^*], \tag{17}$$

where $AF_2(w_2)$ [for " adjustment factor for the second job wage density evaluated at w_2] is the term in brackets in [16] and $h(x)$ is the hazard function associated with the distribution F evaluated at x, or $h(x) \equiv f(x)/\tilde{F}(x)$.

By induction we can construct the marginal density of wages associated with the k^{th} job in an employment spell as

$$f_k(w_k) = \frac{f(w_k)}{\tilde{F}(w^*)} AF_k(w_k)\, \chi[w_k > w^*], \tag{18}$$

where the adjustment factor $AF_k(w_k)$ is defined recursively by

$$AF_k(w_k) = \int_{w^*}^{w_k} AF_{k-1}(x)\, h(x)\, dx. \tag{19}$$

To derive the weights $q_1, q_2, \ldots$ referred to in the text, we proceed as follows. Consider the *conditional* [on employment] steady state distribution of spell orders, Q, where $Q(k)$ gives the probability that a randomly sampled employed individual is in his k^{th} job spell. We derive this distribution in two steps. First we determine the probability that a randomly-selected employment spell ends after exactly k jobs, and we denote this probability distribution by R. An individual in his first job spell who is employed at wage w_1 exits into another job at rate $\lambda_e \tilde{F}(w_1)$ and exits into nonemployment [i.e., is "involuntarily" separated from this job] at rate η. Then conditional on his wage, the likelihood that the employment spell ends after the first job is the likelihood that the first job ends due to a dismissal, which is $\eta/(\eta + \lambda_e \tilde{F}(w_1))$. Then the unconditional probability of an employment spell ending after one job is

$$R(1) = \int_{w^*} \frac{\eta}{\eta + \lambda_e \tilde{F}(w_1)} f_1(w_1)\, dw_1. \tag{20}$$

Conditional on not having exited an employment spell before the k^{th} job, we have by extension that the probability that the employment spell ends after the k^{th} job [which we will denote $\hat{R}(k)$] is

$$\hat{R}(k) = \int_{w^*} \frac{\eta}{\eta + \lambda_e \tilde{F}(w_k)} f_k(w_k)\, dw_k, \; k = 2, 3, \ldots . \tag{21}$$

Then the unconditional distribution of numbers of jobs in completed employment spells is

$$R(k) = \prod_{j=1}^{k-1} (1 - \hat{R}(j)) \hat{R}(k), \; k = 2, 3, \ldots , \tag{22}$$

with $R(1)$ defined in [20] and $\hat{R}(1) \equiv R(1)$.

The second step in the process involves the computation of the conditional probabilities of being found in job j when sampled *given* that the employment spell contains k $[\geq j]$ jobs. Denote this generic conditional probability by π_{jk}, and define the matrix $\mathcal{P}$ [which is a square upper triangular matrix of countably infinite dimension] by

$$\mathcal{P} = \begin{bmatrix} 1 & \pi_{12} & \pi_{13} & \cdots \\ 0 & \pi_{22} & \pi_{23} & \cdots \\ 0 & 0 & \pi_{33} & \cdots \\ \vdots & \vdots & \ddots & \ddots \end{bmatrix}. \tag{23}$$

The fact that $\pi_{11} = 1$ is definitional.

Consider the determination of the elements in the second column of $\mathcal{P}$. Now the total time spent in employment spells which end after two jobs [denoted $t^{(2)}$] is the sum of the first job spell duration *conditional on the first job ending in a quit* and the second job spell duration *conditional on the second job ending in a dismissal.* Conditional on the wages associated with these two jobs, the spell durations are independently distributed. The conditional expectation of the duration of a two-job employment spell is then

$$\begin{aligned} Et^{(2)}(w_1, w_2) &= \int_0^\infty \int_0^\infty (t_1 + t_2)\, \lambda_e \tilde{F}(w_1)\, \exp(-D(w_1)t_1) \qquad (24) \\ &\quad \times \eta\, \exp(-D(w_2)t_2)\, dt_1 dt_2 \\ &= \int_0^\infty t_1\, \lambda_e \tilde{F}(w_1) \exp(-D(w_1)t_1)\, dt_1 \qquad (25) \\ &\quad + \int_0^\infty t_2\, \eta \exp(-D(w_2)t_2)\, dt_2 \\ &= \lambda_e \tilde{F}(w_1) D(w_1)^{-2} + \eta D(w_2)^{-2}, \qquad (26) \end{aligned}$$

where $D(w)$ is defined as $\lambda_e \tilde{F}(w) + \eta$. Then the unconditional expectation of the duration of a two-job spell is

$$\begin{aligned} Et^{(2)} &= \int_{w^*} \int_{w^*} \left[\lambda_e \tilde{F}(w_1) D(w_1)^{-2} \;+\; \eta D(w_2)^{-2}\right] f_{1,2}(w_1, w_2) dw_1 dw_2 \qquad (27) \\ &= \int_{w^*} \lambda_e \tilde{F}(w_1) D(w_1)^{-2}\, f_1(w_1)\, dw_1 \qquad (28) \\ &\quad + \int_{w^*} \eta D(w_2)^{-2}\, f_2(w_2)\, dw_2. \qquad (29) \end{aligned}$$

To simplify notation, define

$$\mathcal{E}_k \equiv \int_{w^*} \lambda_e \tilde{F}(w_k) D(w_k)^{-2}\, f_k(w_k)\, dw_k \tag{30}$$

and

$$\mathcal{W}_k \equiv \int_{w^*} \eta D(w_k)^{-2}\, f_k(w_k)\, dw_k. \tag{31}$$

Using standard ergodic arguments, the probability of finding an individual in the first job of a two job spell under random sampling is

$$\pi_{12} = \frac{\mathcal{E}_1}{\mathcal{E}_1 + \mathcal{W}_2} \tag{32}$$

and of course $\pi_{22} = 1 - \pi_{12}$. In general, the expected duration of an employment spell which ends after the k jobs is

$$\begin{aligned} Et^{(k)} &= \mathcal{E}_1 + \mathcal{E}_2 + \ldots + \mathcal{E}_{k-1} + \mathcal{W}_k & (33) \\ &= \mathcal{T}_{k-1} + \mathcal{W}_k, & (34) \end{aligned}$$

where $\mathcal{T}_{k-1} \equiv \sum_{i=1}^{k-1} \mathcal{E}_i$. Since the probability of finding an individual in job spell j of an employment spell which contains a total of k jobs is equal to the average duration of job spell j in a k job employment spell divided by the expected duration of a k job employment spell, we have

$$\pi_{jk} = \begin{cases} \frac{\mathcal{E}_j}{\mathcal{T}_{k-1}+\mathcal{W}_k} & \Leftrightarrow \; j = 1, \ldots, k-1; \; k = 2, 3, \ldots \\ \frac{\mathcal{W}_k}{\mathcal{T}_{k-1}+\mathcal{W}_k} & \Leftrightarrow \; j = k; \; k = 1, 2, \ldots \\ 0 & \Leftrightarrow \; j > k; \; k = 1, 2, \ldots \end{cases} \tag{35}$$

Now we can define the probability distribution for finding an individual in the j^{th} job of an employment spell given that they are employed at the random sampling time as

$$Q = \mathcal{P}R. \tag{36}$$

5 Maximum Likelihood Estimation of Labor Market Parameters

We shall now define a maximum likelihood estimator with which we can consistently estimate all [estimable] behavioral parameters. The estimator employed should be thought of as a conditional maximum likelihood estimator since it takes as exogenously determined both the labor market state [nonemployed or employed] and the wage [if employed] associated with the initial spell in the observation period. Thus only the duration of initial spells is treated as endogenous; the only endogenous wage information used is that associated with job spells which begin during the observation period.

We allow for the presence of measurement error in the wage data in the following manner:

$$\tilde{w} = w\varepsilon, \tag{37}$$

where w indicates the "true" wage rate associated with a spell, $\tilde{w}$ is the observed wage, and ε is a random variable which is independently and identically log-normally distributed, so that the density of ε is

$$m(\varepsilon) = \phi((\ln(\varepsilon) - \mu_\varepsilon)/\sigma_\varepsilon)/(\sigma_\varepsilon \varepsilon),\ \varepsilon > 0, \tag{38}$$

where the parameter $\sigma_\varepsilon > 0$ and ϕ is the standard normal probability density function. We restrict the parameters μ_ε and σ_ε so that

$$\begin{aligned} & E(\tilde{w}|w) = w \\ \Rightarrow\ & E(\varepsilon|w) = 1\ \forall\, w \\ \Rightarrow\ & \sigma_\varepsilon = (-2\mu_\varepsilon)^{.5}, \end{aligned} \tag{39}$$

where the last line follows from the fact that the mean of ε is equal to $\exp(\mu_\varepsilon + .5\sigma_\varepsilon^2)$. This condition thus places an implicit restriction on μ_ε, namely, that it must be negative..

In models with only unemployed search, allowance for measurement error in the wage observations is not logically necessary, as is demonstrated in Flinn and Heckman (1982). As pointed out by van den Berg and Ridder (1993), in the case of on-the-job search it is a practical necessity when the data contain cases of job-to-job moves which are associated with a wage decrease. Under the model, when it is assumed that the wage is the only characteristic which distinguishes jobs, such an event would occur with probability zero in the absence of measurement error and the maximum likelihood estimator of the model parameters would be undefined.

Under the recoverability condition defined by Flinn and Heckman (1982), which essentially requires that the analyst fix the lower support of the wage offer distribution when the wage offer distribution is assumed to belong to some given parametric family, all the parameters of the on-the-job search model are identified with the exception of the discount rate ρ and the cost of search b. With ρ fixed, all remaining parameters are identified. We now turn to the specification of the likelihood function.

For purposes of writing down the likelihood in a succinct fashion, it will make sense to break the data for each individual into components we will refer to as "cycles."[7] A cycle is demarcated by the occurrence of a nonemployment spell. Then cycles are defined over the observation period as follows. If an individual begins the sample period in the nonemployment state, he remains in that cycle until such time as he leaves the initial spell of nonemployment and enters a new one. Since every nonemployment spell ends in employment, the individual remains in the same cycle through all successive jobs he holds after the initial nonemployment spell [given that all job-to-job transitions are direct]. If an individual begins the observation period in a job, he remains in the original

[7]This follows Wolpin (1992),

cycle until such time as he experiences a nonemployment spell. In theory an individual can experience an indefinitely large number of cycles over any finite-length sample period. We will let C_i denote the number of cycles experienced by sample member i over the sample period.

For reasons of computational tractability we will utilize duration and wage information only from the first two jobs in each cycle. This will not affect the consistency properties of the estimators, though throwing away information will lead to an efficiency loss. The likelihood function will incorporate information pertaining to whether a second job spell completed during the observation period is followed by another job spell or nonemployment.

In defining the likelihood function we will utilize the following notation [the individual subscript i has been dropped for notational simplicity]:

$$
\begin{array}{ll}
\chi_{n,c} & \text{equal to 1 if there is a nonemployment spell in cycle } c \\
\chi_{1,c} & \text{equal to 1 if there is a first job in cycle } c \\
\chi_{2,c} & \text{equal to 1 if there is a second job in cycle } c \\
\chi_{3,c} & \text{equal to 1 if there is a third job in cycle } c \\
t_{n,c} & \text{duration of nonemployment spell in cyle } c \\
t_{1,c} & \text{duration of first job in cycle } c \\
t_{2,c} & \text{duratin of second job in cycle } c \\
\tilde{w}_{1,c} & \text{observed wage in first job in cycle } c \\
w_{2,c} & \text{observed wage in second job in cycle } c \\
r_{n,c} & \text{equal to 1 if the nonemployment spell in cycle } c \text{ is censored} \\
r_{1,c} & \text{equal to 1 if the first job spell in cycle } c \text{ is censored} \\
r_{2,c} & \text{equal to 1 if the second job spell in cycle } c \text{ is censored}
\end{array}
\qquad (40)
$$

Whenever a variable is undefined in a particular cycle [for example, if there is no second job spell in the cycle then $t_{2,c}$, $w_{2,c}$, and $r_{2,c}$ are undefined] we set it equal to zero by convention. Note that the indicator variables for the presence of right-censoring need only be defined for the last cycle in the observation period [C_i. for each i].

In the absence of initial conditions problems, the likelihood contribution for a given individual can be written as:

$$
\begin{aligned}
l \;=\; & \prod_{c=1}^{C} \int_{w^*} \int_{w_1} \left\{ h_n^{1-r_{n,c}} \exp(-h_n t_{n,c}) \right\}^{\chi_{n,c}} & (41) \\
& \times \left\{ \exp(-D(w_1) t_{1,c}) \left[(\lambda_e \tilde{F}(w_1))^{\chi_{2,c}} \, \eta^{1-\chi_{2,c}} \right]^{1-r_{1,c}} m(\tilde{w}_{1,c}/w_1)/w_1 \right\}^{\chi_{1,c}} \\
& \times \left\{ \exp(-D(w_2) t_{2,c}) \left[(\lambda_e \tilde{F}(w_2))^{\chi_{3,c}} \, \eta^{1-\chi_{3,c}} \right]^{1-r_{2,c}} m(\tilde{w}_{2,c}/w_2)/w_2 \right\}^{\chi_{2,c}} \\
& \times \frac{f(w_2)}{\tilde{F}(w_1)} \frac{f(w_1)}{\tilde{F}(w^*)} \, dw_2 \, dw_1, & (42)
\end{aligned}
$$

where $D(w) \equiv \eta + \lambda_e \tilde{F}(w)$ and $h_n \equiv \lambda_n F(w^*)$. Note that $m(\tilde{w}_{j,c}/w_j)/w_j$ is the density of the observed wage in the j^{th} job in the cycle under the measurement error specification [37] and [38]; the term w_j^{-1} is the Jacobian of the transformation.

As discussed above, at least in the case of the Italian data, we do not have the information available which would allow us to use [41] to estimate model parameters. The problem is with the first cycle in the sample. When this cycle begins with the sample member in the employment state, we do not know which job spell he is in. One obvious way to treat this problem is simply to drop the first cycle from estimation for any sample member who begins the observation period in the employment state.[8] This is not a practical option since the majority of sample members occupy only one job during the entire observation period and hence too much sample information would be lost.

The approach we take here is simply to condition on the first observed wage for those individuals who begin the observation period in the employment state. Recall that for these individuals we do not know the order of the job spell in which they begin the sample period. Under our measurement error assumptions, we do know that the true wage is related to the observed wage as follows:

$$w = \tilde{w}/\varepsilon. \tag{43}$$

Then the density of the "true" wage in the sampled job spell is

$$\frac{m(\tilde{w}_s/w_s)\tilde{w}_s/w_s^2}{\Gamma(\tilde{w}_s)}, \ w_s > w^*, \tag{44}$$

where the s subscript denotes sampled spell, the term $\tilde{w}_s/w_s^2$ is the Jacobian of the transformation, and $\Gamma(\tilde{w}_s)$ is a normalizing constant which ensures that the density integrates to unity.

Given the true wage in the sampled spell, the distribution of the wage in any immediately successive spell is $f(w')/\tilde{F}(w_s)$, $w' > w_s$. Conditional on the true wage associated with any sampled employment spell the duration distribution of the sampled employment spell from the sampling time until the completion of the spell [$\vec{t}$] is given by

$$D(w_s)\exp(-D(w_s)\vec{t}, \tag{45}$$

which is identical to the population density of conditional [on the wage rate] job spell durations since the population distribution is exponential. If the sampled job spell is not completed by the end of the observation period, the probability of this event conditional on the wage is given by $\exp(-D(w_s)T)$, where T is the length of the observation period. For a sampled *nonemployment* spell which is completed before T the likelihood contribution is $h_n \exp(-h_n\vec{t})$ and if such a spell is incomplete the contribution is $\exp(-h_nT)$. Due to the stationarity of the model, the densities and survivor functions associated with the forward recurrence times

[8]Since all individuals are assumed homogeneous such a procedure would not create problems of endogenous sampling.

of the sampled spells are exactly the same as their population counterparts. Thus the only change in the likelihood function [41] which is required is the substitution of the sampled wage density [44] for the population density of the wage associated with the first job in the first cycle in the observation period when the first cycle begins with a job spell.

In terms of the parameterization of the likelihood function, we have directly estimated the set $\{\lambda_n, \lambda_e, w^*, \alpha(F), \eta, \mu\}$. Thus the reservation wage characterizing the decision rule of nonemployed individuals is treated as a parameter. As was done in Flinn and Heckman (1982), given estimates of this set of parameters and an assumption concerning the instantaneous discount factor ρ and the m.l. estimates, the point estimate of b is found as follows.[9] For notational simplicity define $A(w) = \int_w V_e(x)dF(x)$ for $w \geq w^*$. Now we can write the value of search as

$$V_n = \frac{b + \lambda_n A(w^*)}{\rho + \lambda_n \tilde{F}(w^*)}, \tag{46}$$

or alternatively we can express it as

$$\begin{aligned} V_e(w^*) &= V_n \\ \Rightarrow V_n &= \frac{w^* + \eta V_n + \lambda_e A(w^*)}{\rho + \eta + \lambda_e \tilde{F}(w^*)} \\ \Rightarrow V_n &= \frac{w^* + \lambda_e A(w^*)}{\rho + \lambda_e \tilde{F}(w^*)}. \end{aligned} \tag{47}$$

Note that in [47], given the reservation wage the value of nonemployment is not a function of b. We can substitute [47] into [6] to get

$$V_e(w) = \frac{w + \eta \left[\frac{w^* + \lambda_e A(w^*)}{\rho + \lambda_e \tilde{F}(w^*)}\right] + \lambda_e A(w)}{\rho + \eta + \lambda_e \tilde{F}(w)}. \tag{48}$$

Call the right hand side [RHS] of [48] $S(V_e, w^*)$. Then we can solve the integral equation $V_e = S(V_e, w^*)$ using m.l. point estimates of all required structural parameters, the m.l. estimate of w^*, and the assumed value of ρ; call the solution of the integral equation $\hat{V}_e$. Finally, we can solve for b using

$$b = \left[\frac{\rho + \lambda_n \tilde{F}(w^*)}{\rho + \lambda_e \tilde{F}(w^*)}\right] [w^* + \lambda_e A(w^*)] - \lambda_n A(w^*). \tag{49}$$

The "smoothness" of the RHS(49) insures that the invariance property of maximum likelihood estimators holds. Thus the estimate of b obtained by substituting

[9]It should be noted that the model estimated in Flinn and Heckman made no allowance for on-the-job search [that is, $\lambda_e = 0$], so that the explicit expression for $\hat{b}$ was substantially different.

m.l. point estimates into [49], including the estimated function V_e, is consistent and has a $\sqrt{N}$ asymptotic normal distribution.

6 Structural Parameter Estimates and Simulation Exercises

It is by now well-known that policy inferences drawn from estimates of structural search models are quite sensitive to assumptions regarding the wage offer distribution F. It is unfortunate that parametric assumptions are required to estimate the model and hence are untestable. To gauge the sensitivity of our inferences to parametric assumptions we estimated the model assuming two different population distributions of wage [or monthly earnings] offers. The distributions considered were the half-normal [i.e., a mean 0 normal distribution truncated from below at 0] and the Pareto.[10] The half-normal distribution satisfies the recoverability condition , while the Pareto does not [because of its unidentified lower bound of its support]. We "fixed" the recoverability problem with the Pareto by defining the lower bound of its support to be equal to the reservation wage in the nonemployment state.

Table 2 contains estimates of the search model for the Italian sample when the remuneration measure is the hourly wage. We might begin by noting the variation in the offer arrival rates across the two distributional assumptions. The Pareto exhibits the lowest arrival rates since, by setting the lower bound of the support equal to the reservation wage, we have ensured that all offers will be accepted. In contrast, the high offer arrival rates under the half-normal assumption in conjunction with the estimated α implies a large proportion of offers are rejected. Estimates of the parameter b [computed under two different assumptions regarding the discount rate] indicate that net benefits associated with being nonemployed are negative, though it should be added that b is quite imprecisely estimated.[11] At the bottom of the table we compute the mean and standard deviation of the population and "acceptable" wage offer distributions [these distributions are the same by construction under the Pareto assumption]. Note that the these two moments are essentially the same under the two distribution assumptions for the acceptable offer distributions.

Table 3 contains estimates of the same model(s) for the U.S., and the contrasts

[10]The half-normal is a one parameter distribution. In our parameterization, the parameter α of the half-normal is the standard deviation of a normal random variate x with mean zero - the half-normal distribution is the truncated distribution of x [truncated from below at 0]. The Pareto is a two parameter distribution. One parameter is the lower bound of the support of the distribution, which under our normalization is the reservation wage. The other parameter is termed α.

[11]We have computed standard errors for the estimator $\hat{b}$ using the delta-method, but do not report them in this version of the paper.

are quite striking. Offer arrival rates in the nonemployed state are estimated to be between 2 to 3 times higher in the U.S. [depending upon the distributional assumption]. Even more striking are differences in the rate of arrival of job offers when employed; in this case the U.S. rates are 10 to 15 times larger [though reassuringly in both countries arrival rates are higher in the nonemployment than in the employment states]. The rates of exogenous separation are also markedly different in the two countries, being over 10 times higher in the U.S. The net benefits associated with being nonemployed are positive under both distributional assumptions. This would seem to be somewhat of a paradox given the fact that a higher proportion of the unemployed live with their parents or other relatives in Italy. Once again however, one should interpret estimates of b very cautiously given the tenuous identifiability of that parameter.

Tables 4 and 5 contain the search model estimates when monthly earnings is used as the remuneration measure. It is interesting to note that under the half-normal distributional assumption the estimated offer arrival rate in the non-employment state is greater in Italy than in the U.S. [though it is very imprecisely estimated], as is the arrival rate of offers when employed. While the half-normal assumption has an associated log likelihood value which is virtually the same as that associated with the Pareto in the Italian sample, the Pareto works slightly better in the U.S. sample. Thus we might give slightly more credibility to the Pareto results in this case.

Using monthly earnings as a compensation measure, the estimated utility flow from nonemployed search becomes positive for the Italian sample under either distributional assumption, whereas the estimated b becomes negative for the U.S. sample under the half-normal assumption. Once again, in all cases we see a close relationship between the estimated mean and standard deviation of the acceptable offer distribution under the two alternative distributional assumptions. This highlights the difficulty of empirically distinguishing between these two, or in fact any two, population wage offer distributions.

We now turn to a consideration of the implications of these estimates for dispersion in lifetime welfare outcomes. The Italian labor market has been characterized as one in which welfare outcomes are " compressed" relative to what is experienced by participants in more competitive markets like that of the U.S. This view is commonly supported by appealing to cross-sectional evidence on wages or earnings like that presented in Figure 1. As we hope has been made clear, such evidence is very difficult to interpret in a life-cycle setting. Our simulation exercise utilizes point estimates of the search models to compute welfare levels associated with a number of labor market careers.

The simulation exercise itself is simple [it is described in detail in the Appendix]. The simulation procedure begins by fixing values for all the structural parameters of the model [the point estimates are used for this purpose]. Each "individual" enters the labor market in the nonemployment state - then a random number is generated which determines the duration of time he spends in the state until finding a job. The wage associated with the first job is determined by another random number draw and the population distribution of [first job] accepted wage offers. Other random numbers are drawn to determine when new offers are received, their values, and the times of exogenous terminations. The process is repeated until the labor market career has lasted at least 45 years [540 months]. For each labor market environment, 10000 sample histories were created. The coefficients of variation reported are computed from these sample distributions.

Table 6 contains estimates of the coefficient of variation for a number of distributions of independent interest. Consider first the top panel of the table, which pertains to hourly wage rates. The first row is the coefficient of variation in hourly wages for individuals employed at the beginning of the observation period, January 1988. These figures have already appeared in Figure 1 and have been commented upon, but it is worth noting again that the cv for the U.S. is about twice as large as the cv for Lombardia. Next consider the results of the structural estimation exercises. When the underlying population distribution function of offers was half-normal, the cv associated with that distribution was essentially identical for the U.S. and Lombardia. The next row presents the cv's associated with the truncated distribution of offers, where the truncation point is the lowest acceptable offer, i.e., the reservation wage. The cv's are very similar in this case as well. The interesting difference arises in the distribution of lifetime welfare. The cv for the lifetime welfare distribution for Lombardia is about three times larger than the cv for the U.S.

When the population offer distribution is assumed to be Pareto, the U.S. cv associated with the offer distribution is about one-fourth larger than the corresponding cv for Lombardia. As was true under the half-normal, the cv for the lifetime welfare distribution is 50 to 100 percent larger for Italy than for the U.S., depending on the discount rate used in the simulations.

The situation with regards to the distribution of monthly earnings is slightly different. In terms of the observed cross-sectional distribution of earnings, the cv for the U.S. is about 150 percent larger than the Italian cv. Under the half-normal assumption, the population offer distributions are estimated to have the same cv for Italy and the U.S. However, the cv for the " acceptable" offer distribution is much higher for the U.S. than in the Italian case. The cv's associated with the welfare distributions are similar for the U.S. and Italy, with the ordering of the two depending on the discount rate used.

Under the Pareto assumption things are very different. The offer distribution has a much larger cv for the U.S. than for Italy. This is also true for the lifetime welfare distribution. Thus the Italian market produces lower levels of lifetime inequality in this case, though we should note that both cv's are quite low, certainly in comparison with the cv's associated with the cross-sectional monthly earnings distribution.

Finally, we consider the coefficients of variation associated with the steady state remuneration distributions derived in Section 4. Since the preferred distributional assumption seems to be the Pareto, we have only computed the steady state wage densities under this distributional assumption. In Table 7 we present a comparison of the coefficients of variation associated with the population wage offer distribution [which is the same as the acceptable wage offer distribution under the Pareto assumption] and those associated with the cross-sectional steady state wage and earnings distributions. With regards to hourly earnings, both for Italy and the U.S. the cv of the SS distribution is about twice as large as the cv for the population wage offer distribution. Thus cross-sectional distributions substantially overstate the amount of *ex ante* inequality individuals face when making draws from this distribution. The situation with regards to monthly earnings is quite similar, though there the cv for the U.S. SS distribution is only about 60 percent larger than the cv for the wage offer distribution. Since the cross-sectional wage offer distributions are linked in a very complicated fashion to lifetime welfare distributions, we are not so interested here in comparing U.S. and Italy coefficients of variation as we are in emphasizing the divergence between inequality in cross-sectional outcome distributions and the *ex ante* uncertainty faced by searchers.

7 Conclusion

The basic story we have told in this paper can be summarized in a few different ways. One lesson which might be drawn concerns the interpretation and comparison of cross-sectional wage or earnings distributions. Recall that in our model labor market the cross-sectional density of wages [or earnings] can be written as

$$f^S(w) = \sum_{i=1}^{\infty} q_i f_i(w), \ w \geq w^*,$$

where $f_i(w)$ denotes the marginal density of wages associated with the i^{th} job in an employment spell. Now these order statistic distributions can be ranked according to a stochastic dominance criterion, so that F_i will first-order stochastically dominate F_j, $j < i$, $i = 2, \ldots$ .If there are no offers received when employed and if the layoff rate is 0, then $q_1 = 1$. While in Lombardia the rate of receiving offers while employed is low, so is the dismissal rate. This serves to produce probability distributions of sampled job orders (q) which are not too dissimilar in the two labor markets. It also produces cv's much higher in cross-sectional remuneration distributions than those associated with the underlying wage offer distributions.

Our results regarding the distribution of welfare levels in the two countries bear out the notion that large amounts of dispersion in cross-sectional wages or earnings are consistent with small amounts of dispersion in lifetime welfare levels. Consider two labor markets X and Y, and assume that market X has no greater dispersion in its distribution of initial [acceptable] wage draws than does

Y. Assume that the rate of offers received by employed workers is greater in Y than in X, as is the [exogenous] dismissal rate. Than while initial disparities in wages will be at least as large in Y as in X, individuals with low [but acceptable] draws will be more likely to move up the wage ladder in Y because of the higher rate of job offers. The higher exogenous separation rate in Y will also serve to limit the length of time individuals who initially receive very high offers can keep them. Thus the greater degree of "dynamics" in market Y will effectively attenuate the stationary wage distribution [or lifetime welfare] distribution from above and below and thus reduce the dispersion in these outcomes. Our estimates lend some credibility to our calling Lombardia market A and the U.S. market B.

Appendix: Simulation Methods

To compute the welfare values $\omega(1), \ldots, \omega(N)$ corresponding to a given set of values for the structural parameters, the procedure used was as follows. All "hypothetical" careers begin in the unemployment state. The discount rate was set to $\rho/12$ [recall that this is a monthly rate], where we set ρ either to .03 or .07. The generic spell is indexed by i, and it begins at time τ_i [$\tau_1 = 0$]. The labor market career is terminated at the conclusion of the first spell with a termination date after the 540^{th} of the career, which corresponds to the individual spending approximately 45 years in the labor market. The instantaneous remuneration rate attached to spell i is denoted r_i, and the type of spell is denoted d_i, where $d_i = 1$ if spell i is an employment spell and is equal to 0 if it is an unemployment spell, and the total duration of the spell is denoted t_i.

If spell i was an unemployment spell [so that $d_i = 0$], we first generated a draw t_i from an exponential distribution with parameter $\lambda_n \tilde{F}(w^*)$. We then generated a wage draw w_{i+1} [since this wage is associated with the $i + 1^{st}$ spell] from the *accepted* wage offer distribution $F(w|w \geq w^*)$. The contribution of spell i to lifetime welfare is given by

$$V_i = \exp(-\rho\tau_i) \int_0^{t_i} b \exp(-\rho u)\, du \tag{50}$$

$$= \rho^{-1} \exp(-\rho\tau_i)[1 - \exp(-\rho t_i)]\, b \tag{51}$$

The next [employment] spell would then begin at calendar time $\tau_{i+1} = \tau_i + t_i$ at the wage w_{i+1}.

If spell i is an employment spell the procedure is essentially the same except for the fact that there are two ways to exit the spell, either through an exogenous separation or a quit into a higher-paying job. Let the wage associated with the job be given by w_i. We first took a draw from an exponential distribution with parameter $\eta + \lambda_e \tilde{F}(w_i)$, which gave us the duration of the employment spell, t_i. We then generated a draw x from a uniform distribution on the unit interval. If $x < \eta/(\eta + \lambda_e \tilde{F}(w_i)$ the spell was considered to have ended in a dismissal so that spell $i+1$ is a nonemployment spell; conversely, if $x \geq \eta/(\eta + \lambda_e \tilde{F}(w_i))$ the next spell was an employment spell. When spell $i+1$ was an employment spell, a wage rate was generated from the distribution $F(w|w > w_i)$. Given spell i is an employment spell, its contribution to lifetime welfare is

$$V_i = \rho^{-1} \exp(-\rho\tau_i)[1 - \exp(-\rho t_i)]\, w_i. \tag{52}$$

Let N denote the number of spells which commenced prior to the 540^{th} month. Say that this history has been generated for "individual" j. Then individual $j's$ labor market career has value

$$\omega(j) = \sum_{i=1}^{N} V_i \tag{53}$$

under the particular set of structural parameter values utilized in the experiment.

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Table 1: Descriptive Statistics for Lombardia and U.S. Samples

Characteristic	Lombardia	U.S.
Sample size	395	1521
Nonemployment		
Some	59 (.149)	432 (.284)
Always	14 (.035)	13 (.009)
Employment		
Same job all 17 months	324 (.820)	846 (.556)
Two or more employment spells	16 (.041)	535 (.352)
Two or more consecutive jobs	12 (.750)	389 (.727)
Wage gain	11 (.917)	255 (.656)

Table 2: Hourly Wage Search Model: Italy

	Hourly Wage Distribution	
Parameter	*Half Normal*	*Pareto*
λ_n	.551	.073
	(.364)	(.011)
λ_e	.040	.006
	(.033)	(.002)
w^*	5.780	5.874
	(.427)	(.246)
$\alpha(F)$	3.846	4.884
	(.617)	(.956)
η	.0016	.0016
	(.0005)	(.0005)
μ_ε	-.019	-.102
	(.007)	(.004)
$\mathcal{L}$	-429.269	-424.890
$b\ (\rho = .03)$	-11.216	-9.682
$b\ (\rho = .07)$	-5.532	-4.366
$E(w)$	3.069	7.386
$SD(w)$	2.318	1.533
$E(w \mid w \geq w^*)$	7.465	
$SD(w \mid w \geq w^*)$	1.486	

Table 4: Monthly Earnings Search Model: Italy

	Monthly Earnings Distribution	
Parameter	*Half Normal*	*Pareto*
λ_n	10.222	.073
	(6.064)	(.011)
λ_e	1.104	.009
	(.626)	(.004)
Y^*	10.737	10.969
	(.401)	(.796)
$\alpha(F)$	3.992	11.958
	(.254)	(7.575)
η	.0016	.0016
	(.0004)	(.0005)
μ_ε	-.025	-.025
	(.005)	(.006)
$\mathcal{L}$	-449.261	-449.552
b ($\rho = .03$)	.827	3.393
b ($\rho = .07$)	3.701	5.456
$E(Y)$	3.185	11.970
$SD(Y)$	2.406	1.002
$E(Y\|Y \geq Y^*)$	11.961	
$SD(Y\|Y \geq Y^*)$	1.138	

Table 5: Monthly Earnings Search Model: U.S.

	Monthly Earnings Distribution	
Parameter	*Half Normal*	*Pareto*
λ_n	.701	.237
	(.166)	(.010)
λ_e	.235	.098
	(.074)	(.007)
Y^*	9.828	10.939
	(.860)	(.430)
$\alpha(F)$	10.258	3.680
	(.825)	(.300)
η	.019	.019
	(.001)	(.001)
μ_ε	-.183	-.175
	(.010)	(.008)
$\mathcal{L}$	-9187.9908	-9184.957
$b\ (\rho = .03)$	-4.379	.958
$b\ (\rho = .07)$	-4.120	.942
$E(Y)$	8.185	15.021
$SD(Y)$	6.184	4.246
$E(Y\|Y \geq Y^*)$	15.302	
$SD(Y\|Y \geq Y^*)$	4.634	

Table 6: Coefficients of Variation for Wage, Income, and Welfare Distributions

Remuneration Measure	**Italy**	**U.S.**
Hourly Wages:		
Observed (1/88)	.327	.621
Half Normal:		
Offer	.755	.756
Acceptable Offer	.199	.220
Lifetime Welfare ($\rho = .03$)	.258	.097
Lifetime Welfare ($\rho = .07$)	.241	.108
Pareto:		
Offer	.208	.246
Lifetime Welfare ($\rho = .03$)	.323	.160
Lifetime Welfare ($\rho = .07$)	.276	.181
Monthly Earnings:		
Observed:	.247	.620
Half Normal:		
Offer	.755	.756
Acceptable Offer	.095	.303
Lifetime Welfare ($\rho = .03$)	.149	.131
Lifetime Welfare ($\rho = .07$)	.101	.146
Pareto:		
Offer	.084	.283
Lifetime Welfare ($\rho = .03$)	.142	.204
Lifetime Welfare ($\rho = .07$)	.093	.218

Table 7: CVs for Accepted and Steady State Wages

Country and Measure	**Acc. Wage Offer**	**SS Wage**
Italy; Hourly Wages	.208	.412
U.S.; Hourly Wages	.246	.482
Italy; Monthly Earnings	.084	.154
U.S.; Monthly Earnings	.283	.423

Figure 1.a
Hourly Wages: Italy

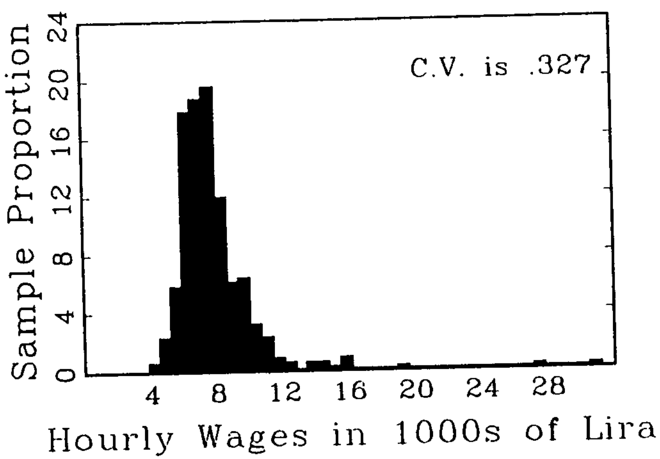

Figure 1.b
Monthly Earnings: Italy

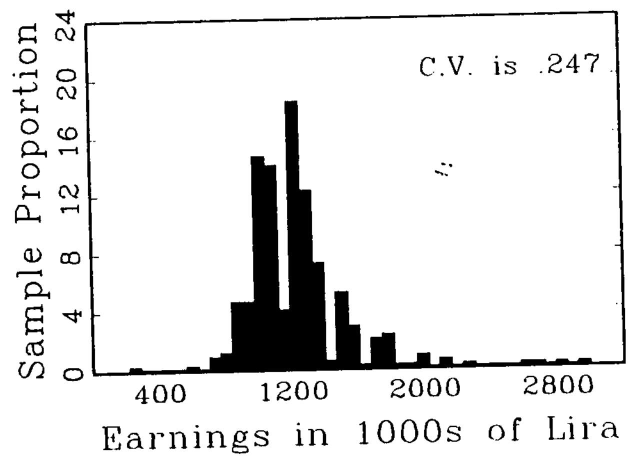

Figure 1.c
Hourly Wages: U.S.

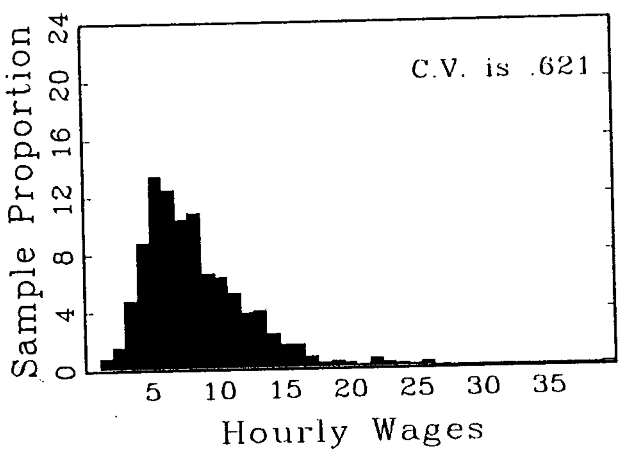

Figure 1.d
Monthly Earnings: U.S.

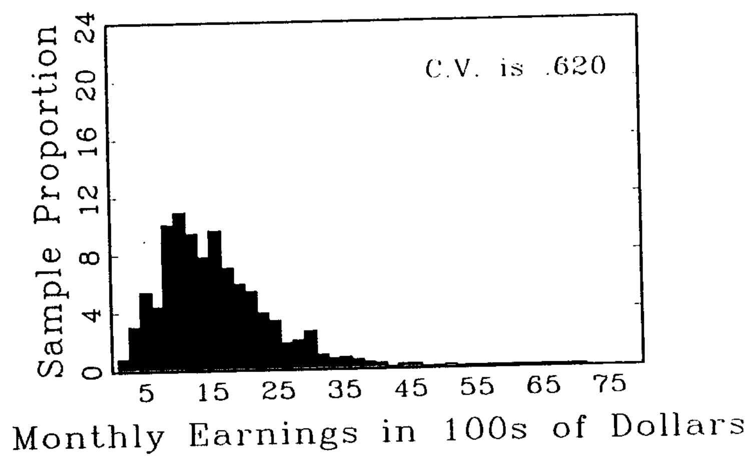

Figure 2

Illustration of an Initial Conditions Problem with Wages Associated with Spells in Progress January 1988

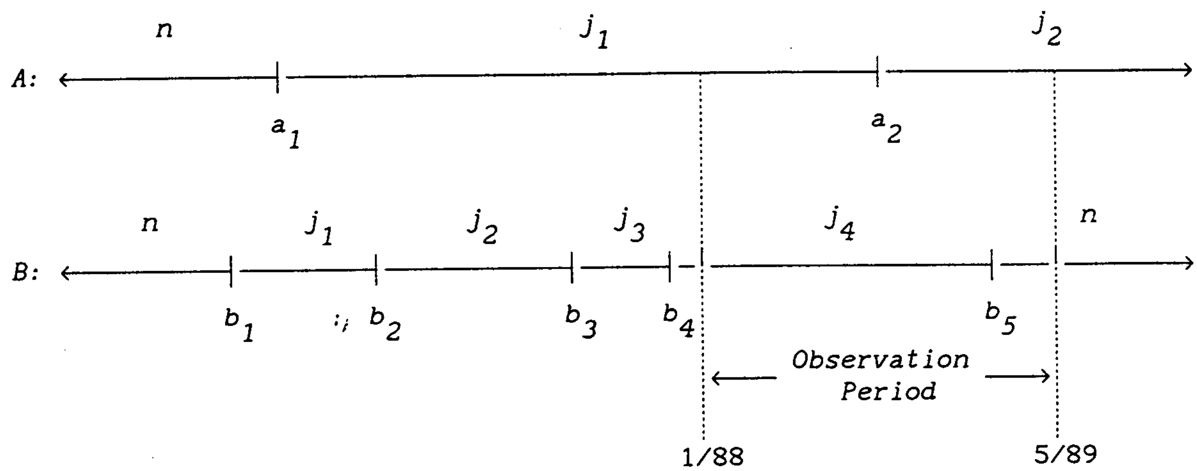

Figure 3
Wage Densities by Job Spell

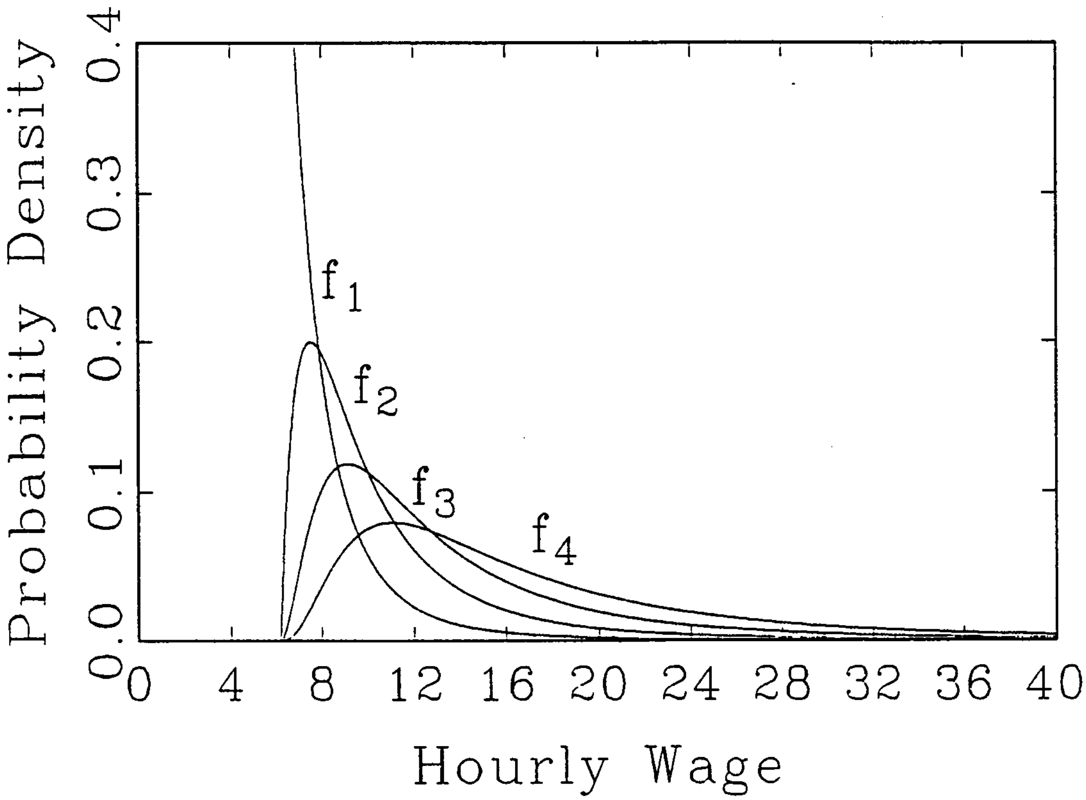

Figure 4
Steady State Density
(Pareto Offer Density)