

# Sources of Earnings Inequality: Estimates from an On-the-Job Search Model of the U.S. Labor Market\*

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## Abstract

Since the early 1980s the labor market in the United States has seen a substantial increase in earnings dispersion. We study the issue by developing an on-the-job search model of the US labor market that allows for wage and employment mobility as a result of optimal individual behavior. We estimate its structural parameters on PSID data at different points in time to clarify the sources of the evolution of earnings inequality and instability between 1987 and 1996. This procedure allows to: compute lifetime measure of inequality on top of the usual cross-sectional measure of inequality and provide counterfactual experiments that evaluate the contribution of different parameters to changes over time by taking into account some equilibrium effects. We find that the increase in lifetime inequality and in cross-sectional inequality have been generated by different sources and that these sources are different by skills: changes in the wage offer distribution are the main determinant of the increase in inequality for skilled workers while both mobility changes and wage offer distribution changes are needed to explain changes for the unskilled.

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# 1 Introduction

Since the early 1980s the labor market in the United States has seen a substantial increase in earnings dispersion. A substantial part of the inequality literature has documented this fact using cross-sectional methods and data.<sup>1</sup> While these contributions are certainly useful we emphasize three main limitations: first, that earnings inequality is not simply described by cross-sectional measures but also by mobility across jobs and labor market states; second, that inequality in labor market outcomes at a given point in time is different from lifetime inequality; and third, that lifetime inequality is arguably a more relevant concept than cross-sectional inequality when judging the overall welfare of an individual worker.

We are clearly not the first to point out the limitations of using only cross-sectional methods to assess individual welfare. By definition individual lifetime welfare depends not only on the position occupied at a given point in time but also on the evolution of such position over time. Various streams of literature have studied this dynamic aspect.

A first group of contributions decompose the overall wage variability in a transitory (over time) component and in a permanent component. One of the first and most influential contribution in this literature, Gottschalk and Moffitt (1994), argues that the increase in the variance of the transitory component of earnings has been an important contributor to the rise in overall earnings inequality.<sup>2</sup> A second group of contributions has the similar objective of assessing the stability of an individual in a given point of the inequality distribution over time but accomplish it by using transition probabilities among quintiles (Buchinsky and Hunt 1999; Cardoso 2006). The main conclusions suggest a decline in mobility over time.

A third and quite large and influential group of works focuses on mechanisms that insure individuals against risk. An important contribution of this literature is the realization that individuals may reduce the volatility of the resources available to them with respect to earnings volatility by adopting risk sharing mechanisms and by using specific institutions. From an empirical point of view, this means focusing on consumption and household-level variables and not only on individual earnings.<sup>3</sup> A fourth group of contribution share a similar con-

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<sup>1</sup>For a recent contribution see Autor, Katz and Kearney 2008; for a recent contribution focusing on various components of cross-sectional inequality (from the usual individual earnings to household disposable income to consumption) see Heathcote, Perri and Violante (2009); for a summary of the main trends over the last forty years see Eckstein and Nagypal (2004); for a frequently cited survey see Katz and Autor (1999).

<sup>2</sup>More recently Gottschalk and Moffitt (2002) suggest an equal increase in the variance of the permanent and transitory components of earnings. Contributions in this line of research that have looked at other countries include Baker and Solon (2003) for Canada and Dickens (2000) for the UK.

<sup>3</sup>Attanasio and Davis (1996) and Blundell and Preston (1998) are among the first and most influential contributions; Blundell and Pistaferri (2003) is an example of an application to a specific institution and Jappelli and Pistaferri (2006) is an example of an application to a country different than the US. Low, Meghir and Pistaferri (2008) propose one of the most complete models in this line of research making it closer to the fifth group of contributions

cern but with a different methodology and a stronger focus on macroeconomic fluctuations and implications. For example both Krueger and Perri (2006) and Heathcote, Storesletten and Violante (2008) model risk and are concerned with the difference between income and consumption inequality.

All these contributions are interesting but they mainly focus on how different types of shocks may impact the individual position in the inequality distribution. The first two groups accomplish this by an essentially statistical decomposition of the data while the second two groups exploit the structure of behavioral models over the life-cycle. Instead, a fifth, and much smaller, group of contributions develops and estimate models that explicitly allow for wage and employment mobility as a result of optimal individual behavior. By estimating the structural parameters of the model, they are then able to construct lifetime measures of inequality taking into account all the individual component of earnings “instability”: cross-sectional inequality, mobility and risk. Flinn (2002) estimates an on-the-job search model of the labor market on Italian and US data showing how the ranking of inequality between the two countries is very different if we look at lifetime inequality rather than simply at cross-sectional inequality. However, he does not assess the evolution of inequality over time. This is the focus of Bowlus and Robin (2004) who develop an innovative non-stationary model of job mobility: they conclude that the main sources of changes in lifetime inequality are changes in job mobility and in the earnings distribution. Mabli (2008) also looks at the evolution of inequality over time but at household level and by estimating over time a two agent on-the-job search model. He concludes that lifetime welfare inequality has experienced a much slower increase than household earnings inequality.<sup>4</sup>

We share the objective and the general methodology of this last group of contributions but we estimate a more standard on-the-job search model. The advantage is that we can estimate by maximum likelihood all its structural parameters and that we have enough data information to estimate the model roughly at the beginning and at the end of a period of significant increase in inequality in the US. We also focus on decomposing the increase in inequality in two main sources: an underlying (possibly demand-driven) wage offer distribution and a set of shocks responsible for mobility opportunities across labor market states and jobs. We are then not only able to build lifetime inequality measures but also to generate counterfactual labor market careers to give a quantitative assessment of which of these components are responsible for the increase in inequality, once equilibrium effects are taken into account. Clearly, decomposing earnings instability in a component directly related to the wage offer distribution and in a pure mobility component does not give a complete characterization of the primitive process at work but helps to disentangle some of the ambiguities present in the literature in particular when linked to a measure

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discussed in this review.

<sup>4</sup>Another set of contributions share the objective of explaining wage inequality by estimating models of labor market mobility: Heckman, Lochner and Taber (1998) and Lee and Wolpin (2008). They both estimate the structural parameters of dynamic general equilibrium models but they do not focus on lifetime inequality measures.

of overall lifetime inequality.

We propose an on-the-job search model of the labor market where individuals sample for jobs and jobs are fully characterized by a wage rate. Wages are extracted from an exogenous wage offer distribution which is the first primitive of the model. Mobility is characterized by endogenous components - the optimal decisions of workers to accept or reject a job offer - and by exogenous components - a set of shocks characterized by exogenous parameters. These shocks parameters are the second set of primitive parameters we are interested in identifying and estimating.

The estimation sample is extracted from a specific section of the *Panel Study of Income Dynamics* (PSID). This section, that we call the *Calendar Section* of the PSID, is particularly appropriate to estimate an on-the-job search model because collects the ending wage in the previous job and the starting wage in the following job every time a job-to-job transition occurs. We generate two estimation samples: one at the beginning (1988-1990) and one at the end (1995-1997) of the period over which the calendar section was collected .

Estimation is performed by maximum likelihood and the identification requires some restrictive but standard parametric assumptions. We estimate two specifications of the model - with and without measurement errors - on skilled and unskilled workers on the two periods. The estimated sampling wage distribution is characterized by an increase in variance for skilled workers and a decrease for unskilled workers. Mobility parameters changes are also very different across skills: for example termination rates of jobs increase on the skilled sample and decrease for the unskilled; arrival rates are stable over time on the skilled sample but increase on the unskilled sample.

Counterfactual experiments help to clarify the impact of the parameters on the change of inequality over time by taking into account some equilibrium effects (essentially the change in the reservation wage). We consider two sets of counterfactual experiments: one in which we change the wage distribution parameters and one where we change the mobility parameters. Two main results arise. First, the sources of the increase in cross-sectional inequality and in lifetime inequality are quite different. Second, there are significant asymmetries across skills. Specifically, the wage distribution is responsible for all the cross-sectional variation change and most of the lifetime variation change for the skilled sample. On the unskilled sample, mobility is able to explain changes in cross-sectional inequality but not in lifetime inequality while exactly the opposite is true for the wage distribution. We also find that the within skills component is becoming more important in explaining the overall cross-sectional and lifetime inequality over the period.

The paper proceeds as follows: section 2 presents the model, section 3 describes the data, section 4 discusses identification and estimation, section 5 and 6 present respectively the results and the counterfactual experiments; section 7 concludes.

## 2 Model

We work with a relative standard on-the-job search model of the labor market.<sup>5</sup> Within the class of search model it is a model that has proved to be quite good at fitting the data and complex enough to capture the main determinants of the labor market dynamics. The model is developed from the workers' point of view since we will only have access to supply side data. Firms behavior is simply described by the presence of a wage offer distribution.

### 2.1 Environment

We work in continuous time within a stationary environment. Agents are infinitely lived, discount utility at the rate  $\rho$  and at each moment in time they occupy one of the following labor market states: Employment or Unemployment. Unemployed workers search for jobs while receiving (dis)utility  $b$  and meet wage offers following a Poisson process with rate  $\lambda_U$ . A wage offer is described as a draw from an exogenous and fixed probability distribution  $G(w)$ . Employed workers still look for jobs, meeting wage offers at a Poisson rate  $\lambda_E$  sampled from the same probability distribution  $G(w)$ . However they may also receive the conventional job destruction shock with Poisson rate  $\eta$  or receive a *reallocation* shock (Jolivet, Postel-Vinay and Robin, 2006) with Poisson rate  $\lambda_R$ .

The presence of a reallocation shock is the only non-standard feature of our model. This shock forces the worker to leave the current job without necessarily transiting through the unemployment state. Formally, she is forced to leave the current job but has the possibility to draw immediately a new wage offer that she may or may not accept. The idea is to describe institutions that generate job-to-job transitions as a consequence of job termination such as the advance notice for fired workers. In terms of data fitting, it is a shock able to describe the significant proportion of job-to-job transitions followed by a wage cut. The frequently used alternative to fit these events is to introduce measurement errors in wages which we will also use in one of our estimated specifications. However, the frequency and credibility of these events in our data make us favor an explicit modelling that can be taken into account in the counterfactual experiments. In other words, we prefer to interpret these transitions as potentially relevant elements of actual job instability and not only as measurement errors in the data. Clearly, our simple modelling strategy is a very partial description of this behavior.<sup>6</sup> First, other situations may generate in the data job-to-job transitions followed by

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<sup>5</sup>It can be defined a partial equilibrium search model with on-the-job search (van den Berg, 1999). The identification of a version of the model without on-the-job search is presented in Flinn and Heckman (1982) while recent estimates with on-the-job search are Flinn (2002) and Jolivet, Postel-Vinay and Robin (2006).

<sup>6</sup>A very interesting literature has been recently developed to account for job-to-job transitions followed by a wage decrease as an explicitly modelled behavior and not as measurement errors. In the presence of bargaining and match-specific productivity, workers may accept lower wages if they expect the job will give them higher rents in the future (Postel-Vinay and Robin, 2002; Flinn and Mabli, 2008).

a wage cut which are very different from a reallocation shock. For example, individuals may evaluate other job characteristics on top of the wage (location, working flexibility). Second, an institution as advance notice is an important example but it introduces a nonstationary element that violates our ex-ante homogeneity assumption: advance notices have a well defined time limit that changes the status of the worker as time passes. Our continuous time model then provides just an approximation under the assumption that advance notices are short enough that receiving a job offer without transiting to unemployment (i.e. receiving a job offer while in the advanced notice period) is approximately equal to receiving a job offer at the same time of the advance notice.

## 2.2 Value Functions and Equilibrium

In this environment workers have to choose if accept or not the wage offers they are presented with. Thanks to stationarity it is convenient to describe workers behavior using value functions. The value of employment for a worker receiving a wage  $w$  is denoted by  $W(w)$  and defined by:

$$\begin{aligned} (\rho + \lambda_E + \lambda_R + \eta) W(w) = & w + \eta U \\ & + \lambda_E \int \max\{W(w), W(w')\} dG(w') \\ & + \lambda_R \int \max\{U, W(w')\} dG(w') \end{aligned} \quad (1)$$

The equation shows that the worker has to transit to unemployment when hit by a job destruction shock and has to decide if accept or reject the new wage offer when hit by an on-the-job wage offer or a reallocation shock. Notice that the outside option is different as a result of these two types of shocks: in the first case it is the value at the current job while in the second case it is the value of unemployment since the current job has been terminated.

The value of unemployment  $U$  is defined by:

$$(\rho + \lambda_U) U = b + \lambda_U \int \max\{U, W(w')\} dG(w') \quad (2)$$

where the worker has to decide if accept or reject wage offers sampled from the exogenous wage distribution  $G(w)$ . It is easy to show that the value of employment (1) is increasing in the current wage while the value of unemployment (2) is constant with respect to wages. The optimal decision rule will then have a reservation value property: the worker will accept a job with wage above a threshold  $w^*$  when facing unemployment and will accept a job with wage above the current wage when employed. Incorporating this optimal behavior in the

previous value functions leads to:

$$\begin{aligned} \left( \rho + \lambda_E \tilde{G}(w) + \lambda_R + \eta \right) W(w) &= w + [\eta + \lambda_R G(w^*)] U \\ &+ \lambda_E \int_w W(w') dG(w') \\ &+ \lambda_R \int_{w^*} W(w') dG(w') \end{aligned} \quad (3)$$

and:

$$\left[ \rho + \lambda_U \tilde{G}(w^*) \right] U = b + \lambda_U \int_{w^*} W(w') dG(w') \quad (4)$$

The reservation values are then obtained by solving:

$$\begin{aligned} w^* &: W(w^*) = U \\ w &: W(w) = W'(w) \end{aligned}$$

leading to:

$$\begin{aligned} w^* &= \left[ \rho + (\lambda_E + \lambda_R) \tilde{G}(w^*) \right] U - (\lambda_E + \lambda_R) \int_{w^*} W(w') dG(w') \\ &= \gamma(w^*) b + [\gamma(w^*) \lambda_U - \lambda_E - \lambda_R] \int_{w^*} W(w') dG(w') \end{aligned} \quad (5)$$

where :

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

The fixed point of equation (5) expresses the reservation wage as a function of the primitive structural parameters of the model therefore concluding the definition of the equilibrium.

A few remarks helps to frame the current model within standard search model of the labor market. Without on the job search and reallocation shock, we expect the equilibrium to converge to the standard partial search model where the reservation wage is simply the discounted value of unemployment. This is easy to show by using equation (3):

$$\lambda_E = \lambda_R = 0 \implies W(w) = \frac{w + \eta U}{\rho + \eta} \implies w^* = \rho U$$

Without on the job search and with a reallocation shock hitting employed workers at the same rate as the wage offers shock hits unemployed workers, we expect the unemployment state to bring no search advantage. Therefore unemployed workers just need to be compensated for their flow value  $b$  when accepting a job:

$$\lambda_E = 0, \lambda_R = \lambda_U \implies \gamma(w^*) = 1 \implies w^* = b$$

The empirical implications of the model are better discussed after presenting the data when we will define the likelihood function and discuss identification.

### 3 Data

To estimate this model we need information on accepted wages and on durations in each state (unemployment durations and employment durations in each job where we observe a wage.) This type of information is not usually available in standard longitudinal data and requires event history data where individuals are observed at least once a month over a sufficiently long period of time. A typical candidate for the US is the *National Longitudinal Survey of Youth* (NLSY). However, we are interested in comparing two representative samples of the U.S. labor market observed at different points in time and the NLSY is ill-suited for this purpose since it only follows particular cohorts.

We have therefore chosen to use the *Panel Study of Income Dynamics* (PSID) which is also the most commonly used dataset to study earnings and job instability over time (Gottshalk and Moffitt, 2002; Jaeger and Stevens, 1999). We focus on a special section (henceforth called *calendar section*) collected in the PSID between the years 1988 and 1997 because only in the calendar section individuals were asked detailed information on monthly labor market status and on hourly wages at the beginning and at the end of each job tenure. Thus, we are able to extract a dataset that allows identification of the structural parameters of the model and that looks quite credible with respect to other data of the U.S. labor market collected in the same period. We explain in details in the data appendix 8.1 below how we have constructed the variables of interest without adding much about the PSID which is a well-known and widely used survey.

Since the calendar section only lasted from 1988 to 1997 and we need at least three years of data to obtain a dataset with sufficiently large sample size, we build two samples: one at the beginning of the period (survey years 1988-1990) and one at the end of the period (survey years 1995-1997).<sup>7</sup> For data limitations due the PSID design we focus only on males head of household aged 20-65. We drop those with less than three years of data and with missing records on the monthly labor market status question. Finally, we keep only individuals in employment or in unemployment at the moment of the interview.

The calendar section of the PSID asks head of households to report their labor market status in each month of the previous calendar year (i.e. data collected in the 1988 survey refer to the period January-December 1987). Employed individuals at the date of the interview are asked to report which months of the previous year they were holding the current job, they are also asked whether they changed job in the previous year and which months of the previous year they were holding the other job. Unemployed individuals at the date of the interview are asked which month of the previous year they were employed in their last job. We use these questions to construct employment durations (denoted  $t_1(i) \dots t_3(i)$  below) and unemployment durations (denoted  $t_u(i)$  below) for each individual.

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<sup>7</sup>It is worth mentioning that the years between 1988 and 1990 and between 1995 and 1997 are at similar points of the business cycle.



The wage information in the calendar section follows a starting wage/ending wage structure particularly appropriate to evaluate wage changes upon job change. Any time an individual engages in a job-to-job transition the calendar section of the PSID records the ending wage in the job just left and the starting wage in the new job just accepted. For example, if a worker leaves the job in which we are first observing him and moves to a new job, the ending wage will be recorded in our data set as  $w_1(i)$  and the starting wage in the new job as  $w_2(i)$ . The starting wage information is collected by PSID every time an individual starts a job during the calendar section period, including individuals that transit in the unemployment state. Therefore, for all the individuals that we first observe as unemployed and that find a job within our window of observation we can record the starting wage of the job accepted immediately after the unemployment spell. Due to identification issues that we will explain in the next section, this starting wage that follows unemployment conveys a different type of information and that is why we label it as  $w_u(i)$  instead of  $w_1(i)$ .

To summarize, in terms of notation, the vector of variables on an individual  $i$  is defined as follows

$$\left\{ \begin{array}{c} w_u(i), w_1(i), w_{k \in \{2, \dots, K\}}(i), \\ t_u(i), t_{k \in \{1, \dots, K\}}(i), \\ c_u(i), c_{k \in \{1, \dots, K\}}(i), r_{k \in \{1, \dots, K\}}(i) \end{array} \right\}_{i=1}^N$$

where:  $w_u(i)$  is the wage in the first job out of unemployment;  $w_1(i)$  is the wage in the first job spell that we observe<sup>8</sup>;  $w_k(i)$ ,  $k = 2, \dots, K$  is the wage in the  $k$ th observed job spell in the cycle;  $t_u(i)$  is the unemployment duration,  $t_k(i)$  is the job spell duration for job  $k$ ;  $c_u(i) = 1$  if the unemployment duration is right censored,  $c_k(i) = 1$  if the employment duration of job  $k$  is right censored,  $r_k(i) = 1$  if the employment duration of job  $k$  terminates in unemployment.

As mentioned our estimation samples only includes males head of household aged 20-65 with at least three years of data that are in the employment or unemployment state. We limit ourself to only one cycle per individual. A cycle is defined as a spell that starts and ends in the unemployment state since the unemployment state “resets” the dynamic process. Moreover, since only very few individuals experience more than three job-to-job transitions over our period of observation and since the computational burden greatly increases with the number of transitions<sup>9</sup> we have decided to use information on at most three consecutive job spells.

We provide descriptive statistics by skill levels because we estimate the model conditioning on skills. Skill is defined on years of schooling. We generate two samples: *skilled* are individuals who have completed some College (more than

<sup>8</sup>But notice that individuals entering our observation period as employed do not report the order of this job spell: namely we do not know if it is a job spell following an unemployment spell or if it is following a number of previous job-to-job transitions. This raises a major initial condition problem that we solve in estimation by conditioning our information set on the first observed job. This issue will be clarified and discussed in more details in section 4.1.

<sup>9</sup>This is due to the many different likelihood combinations that are generated as the number of transitions considered increases. See section 4.1 for a detailed explanation.

15 years of education) and *unskilled* are individuals who have completed less than that (15 or less years of education). We prefer focusing on estimation by skills for the following reasons. First, the model assumes ex-ante homogeneity. Second, the empirical literature emphasizes that the sources of growing inequality are potentially very different at lower skill levels (where for example minimum wages and union coverage are very important) with respect to higher skill levels (where for example technology innovation and social norms seem to become more important). Distinguishing at least two skill levels helps focusing on different potential driving forces of inequality and mobility across skill groups, an issue that was already signalled in Gottschalk and Moffitt (1994). Third, the debate on the so called skill-biased technological change also suggests that the labor market dynamics for skilled and unskilled workers could have been potentially very different over the period under consideration.

Table 1 shows the descriptive statistics on the two samples 1988-1990 and 1995-1997 for the skilled and unskilled. The employment and unemployment tenures are in months and wages are hourly deflated with base January 2000.

We have a valid wage and tenure information on 146 skilled individuals who started in employment or unemployment at the interview date in 1988. In terms of duration, out of the initial 146 spells, 33% of the employment spells are right censored while only 10% of the unemployment spells are right censored ( $c_1 = 1$ ). Their average tenure on the first job spell ( $t_1$ ) is of about 48 months while for those who started in unemployment the average tenure in unemployment ( $t_u$ ) is of 9 months. 86 of the initial 146 had a second job spell ( $t_2$ ) with a wage ( $w_2$ ) of 21.34\$ per hour on average, only 33 find a third job with  $w_3$ ;  $t_2$  is much shorter on average (only 14 months) than  $t_1$  because  $t_2$  is often right censored ( $c_2 = 1$  59% of the times).  $w_2$  is larger than  $w_1$  or  $w_u$  only 53% of the times: this quite large proportion of job-to-job transitions to a lower wage motivates our introduction of a reallocation shock.

The descriptive statistics of the skilled in the period 1995-1997 have the same structure and we highlight only the main differences with respect to the 1988-1990 period. Wages out of unemployment  $w_u$  have an higher mean with respect to 1988 and similar standard deviation, an indication consistent with an increase in earnings stability. Also the higher variance of  $w_2$  wages for individuals entering our window of observation as employed supports this prediction. However,  $w_2$  wages for individuals entering our window of observation as unemployed actually have a lower mean. Unemployment durations  $t_u$  are lower in the window 1995-1997 while employment durations  $t_1$  are higher. Employment durations in the second spell  $t_2$  are similar across the two periods while the proportion of job-to-job transitions followed by a wage loss is smaller in the period 1995-1997 than in 1988-1990.

These descriptive statistics are consistent with comparable data from other sources. Employment tenure is comparable to the estimates provided on CPS and PSID data (using the question on job tenure outside the calendar section) by Jaeger and Stevens (1999) and on NLSY data by Bernhardt et al. (1999). They report an annual separation rate of around 15% which is comparable to our tenure in the second job  $t_2$  (our first job is most of the times left-censored)

of 14 months. The wage information is also comparable to SIPP data reported in Low et al. (2006). They report an average hourly wage for job changers of 14.75\$ in 1993 dollars. Finally, the significant proportion of job-to-job changes followed by a wage loss is also found by Jolivet, Postel-Vinay and Robin (2006).

## 4 Estimation and Identification

Conditioning on the model it is possible to derive the likelihood contributions of the data just described. We will then use these contributions to define a maximum likelihood estimator. We specify and estimate two empirical specification for the model: one without measurement errors in wages, section 4.1, and one with measurement errors in wages, section 4.2.

### 4.1 Likelihood Function without Measurement Errors

The general formulation for duration densities is the following (we will omit the index  $i$  for notational simplicity). If the hazard rate out of a given state ( $h$ ) is constant then the density of completed spells in that state is negative exponential with parameter  $h$ :

$$f(t) = h \exp(-ht), t > 0$$

In the model the hazard rate out of unemployment is:

$$h_u = \lambda_U \tilde{G}(w^*)$$

and the hazard rate out of employment is:

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

The unemployment duration contributions therefore are:

$$\begin{aligned} f_u(t_u) &= h_u \exp(-h_u t_u) \\ f_u(t_u, c_u = 1) &= \exp(-h_u t_u) \end{aligned} \tag{6}$$

The employment duration contributions are the following, where we have to take into consideration that the hazard rate out of employment leads to one of the following three possible outcomes: unemployment, employment to an higher wage, employment to a lower wage. Moreover, we have to consider that some

employment durations are right-censored.

$$\begin{aligned}
f_e(t_k, r_k = 1 | w_k) &= h_e(w_k) \exp[-h_e(w_k) t_k] \frac{\lambda_R G(w^*) + \eta}{h_e(w_k)} & (7) \\
&= [\lambda_R G(w^*) + \eta] \exp[-h_e(w_k) t_k] \\
f_e(t_k, w_{k+1} > w_k | w_k) &= h_e(w_k) \exp[-h_e(w_k) t_k] \frac{(\lambda_R + \lambda_E) \tilde{G}(w_k)}{h_e(w_k)} \\
&= (\lambda_R + \lambda_E) \tilde{G}(w_k) \exp[-h_e(w_k) t_k] \\
f_e(t_k, w_{k+1} < w_k | w_k) &= h_e(w_k) \exp[-h_e(w_k) t_k] \frac{\lambda_R [G(w_k) - G(w^*)]}{h_e(w_k)} \\
&= \lambda_R [G(w_k) - G(w^*)] \exp[-h_e(w_k) t_k] \\
f_e(t_k, c_k = 1 | w_k) &= \Pr(T > t_k | w_k) \\
&= \exp[-h_e(w_k) t_k]
\end{aligned}$$

The first density refers to job spells that terminate in unemployment. The hazard rate of such an event takes into account that two shocks may be its source: an exogenous termination shock or a reallocation shock with a wage draw lower than the reservation wage. The second density corresponds to a job-to-job transition to a higher wage: it may be the result of an on-the-job wage offer or of a reallocation shock with a wage draw higher than the wage at the previously held job. The third density pertains to job-to-job transitions characterized by a wage decrease. As mentioned, in contradiction with a standard on-the-job search model, we observe a significant number of them in the data and we are reluctant to assume only measurement errors as their source. Following Jolivet, Postel-Vinay and Robin (2006), we prefer to introduce a reallocation shock that forces individual to leave their current job but at the same time give them the possibility to immediately draw a new wage. When this new draw is between the previous wage and the reservation wage, we observe a job-to-job transition followed by a wage decrease. In the next section, we will specify a formulation of the empirical model with both a reallocation shock and measurement errors in wages where the observation of a wage drop after a job-to-job transition does not necessarily mean that a reallocation shock has taken place. Lastly, the fourth density describes right-censored job tenures.

Before specifying the likelihood contribution of observed wages, we have to point out the fundamental initial condition issue that we face: for many individuals in the sample - namely all the individuals that enter our observation period in the employment state - the first observed wage is not the first wage out of unemployment. Moreover, given the sample design of the survey, we do not have a credible way to infer the number of previous jobs held outside our window of observation. In other words, we do not know if the first observed wage is the wage from the first job, second job, or the  $k^{th}$  job in the employment spell. This is relevant because conditioning on the model the likelihood contribution of an observed wage at a given job depends on the order of such a job within a

continuous employment spell.<sup>10</sup>

Following Flinn (2002), we opt for a solution very costly in terms of lost information but of straightforward implementation and unaffected consistency properties: we condition on the first wage observed for individuals that enter the observation window in employment and exploit in estimation only the likelihood contribution of the following observed wages (on top of exploiting fully the information from individuals that enter our window of observation in unemployment.)

For this reason we present below the unconditional likelihood of wages observed immediately after a period of unemployment but only the conditional likelihood of wages observed after a period of employment.

$$\begin{aligned}
f_w(w_u) &= \frac{g(w_u)}{\tilde{G}(w^*)} \tag{8} \\
f_w(w_{k+1}, w_{k+1} > w_k | w_k) &= \frac{g(w_{k+1})}{\tilde{G}(w_k)} \times \frac{(\lambda_R + \lambda_E) \tilde{G}(w_k)}{\lambda_E \tilde{G}(w_k) + \lambda_R \tilde{G}(w^*)} \\
f_w(w_{k+1}, w_{k+1} < w_k | w_k) &= \frac{g(w_{k+1})}{\tilde{G}(w^*)} \times \frac{\lambda_R [G(w_k) - G(w^*)]}{\lambda_E \tilde{G}(w_k) + \lambda_R \tilde{G}(w^*)}
\end{aligned}$$

Notice that in the last two densities we have to take into account the probability that a job to job transition may be to a higher or a lower wage.

Consider now the likelihood contribution of a cycle for a typical individual. A cycle is a spell that starts and ends in the unemployment state since the unemployment state “resets” the dynamic process. In this cycle the individual will experience an unemployment duration and some job-to-job transitions before returning back to unemployment. If we observe an individual already in a job spell, the cycle will end when the individual will experience unemployment. For the previously mentioned initial condition problem, we cannot write the likelihood of the first observed job ( $w_1$ ) because we do not know its order in the currently observed cycle.

Once we consider censoring and the possibility of job-to-job transitions leading to a job decrease, the different combinations of possible likelihoods blow up as the number of job spells in a cycle increases. In our sample we observe a maximum of four job spells in a cycle leading to 26 possible different likelihood configurations. To reduce the computational burden and since a negligible number of individuals experiences more than three job-to-job transitions in our observation period we have decided to exploit the information used in the likelihood up to three job spells in a cycle. Moreover, very few individuals have valuable information on more than a cycle and therefore we will use only one cycle for each individual. Note that limiting our information in this way has no impact in terms of identification or asymptotic properties but only reduces efficiency. Despite these simplifications the general expression for the likelihood

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<sup>10</sup>Flinn (2002) is able to show that the non-trivial likelihood that takes into account the job order within an employment spell can have a closed form under appropriate distributional assumptions.

on the entire sample is rather involved and therefore we think it is more instructive to show a couple of specific examples where we denote the parameters to be estimated with the vector  $\theta$ .<sup>11</sup>

*Example 1:*

*Take an individual with:*

$$\{t_u, t_1, t_2, w_u, w_2, w_2 > w_u, r_2 = 1\}$$

*Notice that since we observe  $w_u$  and  $w_2$  and since  $r_2 = 1$  the values on the censoring indicators  $c_u, c_1$  and  $c_2$  are zero by definition and the value of the transition-to-unemployment indicator  $r_1$  is also zero by definition. The resulting likelihood is:*

$$\begin{aligned} L(t_u, t_1, t_2, w_u, w_2, r_2 = 1; \theta) &= f_u(t_u) f_w(w_u) \\ &\quad \times f_e(t_1, w_2 > w_u | w_u) f_w(w_2, w_2 > w_u | w_u) \\ &\quad \times f_e(t_2, r_2 = 1 | w_2) \end{aligned}$$

*Example 2:*

*Take an individual with:*

$$\{t_1, t_2, w_1, w_2, w_2 > w_1, c_2 = 1\}$$

*As before implications for the censoring indicators and for the transition-to-unemployment indicators which are obvious are not explicitly reported. The resulting likelihood is:*

$$\begin{aligned} L(t_1, t_2, w_1, w_2, c_2 = 1; \theta) &= f_e(t_1, w_2 > w_1 | w_1) \\ &\quad \times f_w(w_2, w_2 > w_1 | w_1) \\ &\quad \times f_e(t_2, c_2 = 1 | w_2) \end{aligned}$$

## 4.2 Likelihood Function with Measurement Errors

The applied literature often assumes the presence of measurement errors in wages or earnings. One motivation is the observation of “unrealistically low” wages and for some dataset the availability of validation studies that suggest inconsistency between administrative records of wages and wages actually reported by respondents to survey data (Bound, Brown and Mathiowetz, 2001). Another motivation is the ability of measurement errors to fit some observations in the data that are inconsistent with the assumed model. In the context of on-the-job search model, measurement errors are typically assumed to fit the counterfactual observation of job-to-job transition followed by a wage decrease.<sup>12</sup>

<sup>11</sup>For a detailed version of the likelihood without measurement errors see the Appendix of the working paper version of the paper: Flabbi and Leonardi (2008).

<sup>12</sup>See Flinn (2002) among others.

As mentioned, we think there are too many observations of this kind to beforehand commit to measurement errors as their only source and we prefer a more flexible specification where also a reallocation shock is present. Under the usual assumptions regarding the distributional properties of the measurement error we will show that both the measurement error parameter and the reallocation shock parameter are identified from our data.

The likelihood contribution under measurement errors can be described as follows. Denote the observed wages with  $w^o$ , the true wages with  $w$  and the measurement error with  $\varepsilon$ . The observed wage is then defined by:

$$w^o = w\varepsilon \quad (9)$$

Given the wages density function  $f_w(w)$  and the errors density function  $q(\varepsilon)$ , the implied density function on observed wages will be:

$$f_{w^o}(w^o) = \int_{S(w)} \frac{1}{w} q\left(\frac{w^o}{w}\right) f_w(w) dw \quad (10)$$

where we are integrating out the true wage over its support  $S(w)$  (alternatively we could have integrated out the measurement error). The wage densities described in the no measurement errors case, equations (8), then become:

$$\begin{aligned} f_w(w_u^o) &= \int_{w^*} \frac{1}{w_u} q\left(\frac{w_u^o}{w_u}\right) f_w(w_u) dw_u \\ f_w(w_{k+1}^o | w_k) &= \\ p_H(w_k^o, w_{k+1}^o) &\int_{w_k} \frac{1}{w_{k+1}} q\left(\frac{w_{k+1}^o}{w_{k+1}}\right) f_w(w_{k+1}, w_{k+1} > w_k | w_k) dw_{k+1} \\ + (1 - p_H(w_k^o, w_{k+1}^o)) &\int_{w^*} \frac{1}{w_{k+1}} q\left(\frac{w_{k+1}^o}{w_{k+1}}\right) f_w(w_{k+1}, w_{k+1} < w_k | w_k) dw_{k+1} \end{aligned} \quad (11)$$

Notice the difference on the conditional distribution: now any observed job-to-job transition may have an underlying increase or decrease in true wages. But the two events will have a different probability that depends on the observed wage differential. The probability of a true wage increase is:

$$p_H(w_k^o, w_{k+1}^o) = P\left(\frac{\varepsilon_k}{\varepsilon_{k+1}} > \frac{w_k^o}{w_{k+1}^o}\right) \quad (12)$$

and it is higher the higher  $w_{k+1}^o$  with respect to  $w_k^o$ .

As standard in the literature, we will not assume that durations are observed with measurement errors and therefore their densities are equal to the previous case. As an illustration on how the likelihood with measurement errors is constructed, we consider the two previous examples and specify their likelihood under this different specification.

*Example 1:*

Take and individual with:

$$\{t_u, t_1, t_2, w_u^o, w_2^o, w_2^o > w_u^o, r_2 = 1\}$$

the resulting likelihood is:

$$L(t_u, t_1, t_2, w_u^o, w_2^o, r_2 = 1; \theta) = \int_{w^*} f_u(t_u) \frac{1}{w_u} q\left(\frac{w_u^o}{w_u}\right) f_w(w_u) \left\{ \begin{aligned} & p_H(w_u^o, w_2^o) \int_{w_u} f_e(t_1, w_2 > w_u | w_u) f_e(t_2, r_2 = 1 | w_2) \frac{1}{w_2} q\left(\frac{w_2^o}{w_2}\right) f_w(w_2, w_2 > w_u | w_u) dw_2 \\ & + (1 - p_H(w_u^o, w_2^o)) \int_{w^*} f_e(t_1, w_2 < w_u | w_u) f_e(t_2, r_2 = 1 | w_2) \frac{1}{w_2} q\left(\frac{w_2^o}{w_2}\right) f_w(w_2, w_2 < w_u | w_u) dw_2 \end{aligned} \right\} dw_u$$

Example 2:

Take and individual with:

$$\{t_1, t_2, w_1^o, w_2^o, w_2^o > w_1^o, c_2 = 1\}$$

the resulting likelihood is:

$$L(t_u, t_1, w_1^o, w_2^o, c_2 = 1; \theta) = \int_{w^*} \frac{w_1^o}{w_1^2} q\left(\frac{w_1^o}{w_1}\right) \frac{1}{\Gamma(w_1^o, w^*)} \left\{ \begin{aligned} & p_H(w_1^o, w_2^o) \int_{w_1} f_e(t_1, w_2 > w_1 | w_1) f_e(t_2, c_2 = 1 | w_2) \frac{1}{w_2} q\left(\frac{w_2^o}{w_2}\right) f_w(w_2, w_2 > w_1 | w_1) dw_2 \\ & + (1 - p_H(w_1^o, w_2^o)) \int_{w^*} f_e(t_1, w_2 < w_1 | w_1) f_e(t_2, c_2 = 1 | w_2) \frac{1}{w_2} q\left(\frac{w_2^o}{w_2}\right) f_w(w_2, w_2 < w_1 | w_1) dw_2 \end{aligned} \right\} dw_1$$

where  $\Gamma(w_1^o, w^*)$  is a normalizing constant necessary to obtain a density integrating up to one on its support.

### 4.3 Identification and Estimation Discussion

The identification of the model without and with measurement errors is essentially proved in Flinn and Heckman (1982) and it is very similar to Flinn (2002). It requires to impose a recoverability condition on the distribution of wage offers. Without the recoverability condition only the reservation wage and the hazard rates can be identified. The recoverability condition states that a parametric assumption on the wage offer distribution must be imposed and that the parameters of the chosen distribution should be identified by observing its truncation. When measurement errors are imposed also a parametric assumption on their distribution is required to attain identification.

The only difference with these previous works is the presence of the additional parameter  $\lambda_R$ : the reallocation shock. Its identification is straightforward in the model without measurement errors because it is directly identified by job durations followed by a wage decrease. In the model with measurement



errors the identification is more subtle but still straightforward. Now a job-to-job transition followed by a wage decrease may be due to a reallocation shock only with a probability that depends on the difference between the two wages ( $p_H(w_k^o, w_{k+1}^o)$ ). If without measurement errors any drop in wages as a result of a job transition is imputed to a reallocation shock, now only larger drops in wage have a substantial probability of being due to a reallocation shock. How substantial depends on the magnitude of the measurement errors. Since measurement errors have also another source of identification (the difference between the smallest observed wage and the estimated reservation wage) we can separately identify the reallocation shock parameter and the measurement errors parameter.

Once the parametric assumptions are made, the estimation is by maximum likelihood. Only two remarks in this respect. First, in the no-measurement errors case the reservation wage is a function of parameters but also defines the support of the observed wage distribution violating one regularity condition for maximum likelihood estimation. Flinn and Heckman (1982) suggest the following non-parametric strongly consistent estimator for the reservation wage:

$$\widehat{w}^* = \min_w \{\mathbf{w}\} \quad (13)$$

and then estimation by maximum likelihood on the resulting concentrated likelihood. Second,  $(\rho, b)$  enter the likelihood only through the reservation wage and therefore are only jointly identified. In terms of estimation, given estimates for the other parameters including the reservation wage we can recover  $b$  by exploiting the reservation wage equilibrium equation (5) and by fixing a value for the discount rate  $\rho$ . The details are reported in Appendix 8.2.

The parametric assumptions we choose are the standard assumptions found in the literature.<sup>13</sup> We will assume that  $G(w)$  is a lognormal probability distribution denoted by the two parameters  $(\mu, \sigma)$  and characterized by the following pdf:

$$g(w; \mu, \sigma) = \frac{1}{\sigma w} \phi\left[\frac{\ln(w) - \mu}{\sigma}\right], w > 0$$

When measurement errors are assumed we need an additional parametric assumption on their distribution. Again following the literature we assume them i.i.d. lognormal with parameters  $(\mu_\varepsilon, \sigma_\varepsilon)$ . Their density is therefore:

$$q(\varepsilon; \mu_\varepsilon, \sigma_\varepsilon) = \frac{1}{\sigma_\varepsilon \varepsilon} \phi\left[\frac{\ln(\varepsilon) - \mu_\varepsilon}{\sigma_\varepsilon}\right], w > 0$$

We also assume that the conditional expectation of observed wages is equal to the true wage:<sup>14</sup>

$$E(w^o|w) = w \implies E(\varepsilon|w) = 1$$

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<sup>13</sup>Contributions that assume a lognormal distribution in a similar context are, among others: Eckstein and Wolpin (1995); Dey and Flinn (2005) and Flabbi (2009). Other assumptions are feasible as long as the assumed distribution is recoverable as proved in Flinn and Heckman (1982): Flinn and Heckman themselves assume a normal and an exponential distribution.

<sup>14</sup>This condition corresponds in this environment to the usual zero conditional expectation assumption. For the same assumption see also Flinn (2002).

Under lognormality, this condition imposes a constraint on the parameters ( $\sigma_\varepsilon = \sqrt{-2\mu_\varepsilon}$ ): we can therefore just identify and estimate one of the two. Under these assumptions we can also obtain a particularly convenient expression for the probability of a true wage increase  $p_H(w_k^o, w_{k+1}^o)$ . It is a joint lognormal distribution with parameters 0 and  $\sigma_\varepsilon\sqrt{2}$ .

#### 4.4 Discussion of the Stationarity Assumption

A conventional assumption imposed when estimating search models is that the labor market from which the data are drawn is in a steady state.<sup>15</sup> It is obviously a strong assumption even if some support for it, together with the on-the-job search structure, can be found in the literature.<sup>16</sup> Removing this assumption means that the data are drawn from environments that do not share the same structural parameters and leads to a major identification problem.<sup>17</sup>

In our analysis the assumption is particularly problematic because we are looking at two different points in time and we find them generating different structural parameters.<sup>18</sup> We think there are only two interpretations consistent with this result and with the stationarity assumption. Both imply quite strong assumptions.

First, it is possible that some shocks have hit the structural parameters between the two periods. The shocks should have been unexpected to the individuals and the new steady state should have been reached relatively quickly so that we are in steady state again by the time we observe the individuals in the second period. These assumptions are clearly strong but we think their validity should be evaluated in pragmatic terms. No scholar would really believe that labor markets are stationary forever and therefore any time we estimate a search model assuming stationarity we are making a statement about how far in the past some structural change has taken place so that the approximation error we are making by assuming stationarity is small enough. In our context, this means judging if the two periods under consideration are sufficiently far apart to credibly belong to two different steady states and if the data we pool together to build the two periods are close enough to credibly belong to the same steady state. Our empirical strategy, constrained by the data at our disposal, starts with the first and last year of data available and progressively add data drawn from adjacent years so that the two periods are separated by a

<sup>15</sup>For example, this is the assumption maintained in Flinn and Heckman (1982); Eckstein and Wolpin (1995); Flinn (2002); Flabbi (2009). The assumption is shared by a larger class of structurally-estimated labor market models and by many reduced form applications.

<sup>16</sup>Jolivet, Postel-Vinay and Robin (2006) perform a specification test of stationarity of their on-the-job search model: the test does not reject stationarity on 8 of the 11 countries considered in their study. Flinn and Mabli (2008) perform a stationarity test on a sample of young workers rejecting stationarity. They impute the rejection more to the workers not having reached the steady state portion of their labor market career than to the nonstationarity of the labor market environment.

<sup>17</sup>Bowlus and Robin (2004) and Flinn (2003) attempt a solution to this identification problem within empirically tractable non-stationary search models.

<sup>18</sup>See the Estimation results section.

long enough interval while we can still pool enough observations to estimate the model. Simply using the first and last year or the first two and last two years available is not enough to obtain sufficiently precise estimates: we have therefore decided to use the first three and last three years of data to build the two periods. A three-years time span is in the range used in the literature to define a steady state.<sup>19</sup> Given the structure of the data this also guarantees that at least four years elapse between observations belonging to the two periods. Finally, a three-years time span for each of the two periods gives us the opportunity to perform a small test for stationarity. We examined the equality of three sample characteristics at the beginning and at the end of our three-years samples i.e. in 1988 and in 1990 for the first sample and in 1995 and 1997 for the second sample. The characteristics are the proportion of unemployed and the average and standard deviation of wages of the employed.<sup>20</sup> The Wald test we perform does not reject equality of the moments, resulting in a p-value of 0.319 for the 1995 sample and of 0.285 for the 1988 sample. We read this as an indication that stationarity is not a bad approximation over the three-years intervals.

Second, it is possible that some individuals in the sample are not yet in the steady state portion of their labor market career. If this is the case and if the proportion of individuals in this condition is different between the two periods then we may estimate different structural parameters even if the steady state has remained the same. This would clearly be a quite destructive source of misspecification leading to implausible inference when comparing the two periods. While it is plausible that some individuals may be in this situation we have no reason to believe that their proportion should change over time. To at least partially assess the magnitude of the problem we look at the main demographic characteristics correlated with the probability of being in the steady state portion of the labor market career: potential experience.<sup>21</sup> For the skilled sample on both periods the average experience is about 14 years and more than 90% of the sample has at least three years of experience. For the unskilled, average experience is about 18 years on the 1988 sample and about 17 years on the 1995 sample. More than 97% of the sample has more than three years of experience in both periods. The impression is that our sample is mainly composed by individuals in their mature labor market career stage, making them more likely to be in the steady state portion of their career. Moreover, the differences between the two periods with respect to these demographic characteristics are negligible making less plausible that their difference in parameters estimates might be due to this type of misspecification.

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<sup>19</sup>For example Jolivet, Postel-Vinay and Robin (2006) follow individuals for up to 3 years; Dey and Flinn (2005) for up to 4 years while Flinn (2002) only up to a year and a half due to data limitations on the Italian sample.

<sup>20</sup>We consider only these three moments because most durations cover more than one year. Moreover we pool all the wage together to gain sample size so we cannot differentiate between  $w_u$  and  $w_k$ .

<sup>21</sup>Potential experience is defined as: age- years of schooling - 5.

## 5 Results

### 5.1 Maximum Likelihood Estimation Results

The estimation results are reported in Table 2 for the skilled sample and in Table 3 for the unskilled sample. We present the two specifications, with and without measurement errors, for each of the two periods. Overall the point estimates are in the range of previous estimates in the literature<sup>22</sup> and reasonably precise. Comparing estimates with and without measurement errors the main differences are in the reallocation shock parameter (which becomes irrelevant when measurement errors are present) and in the reservation wages (which are higher when measurement errors are present). The other parameters also change between the two specifications but by a relatively small amount and, most importantly, not so much as to change the comparison across years. In other words, the fact that a parameter increase or decrease between the two periods is robust to the introduction of measurement errors. The exception is the arrival rate of on-the-job offers for the skilled sample: it is estimated to increase between 1988 and 1995 in the specification without measurement errors and to decrease in the specification with measurement errors.

The main differences between the two periods are: (i) the wage offer distribution experiences a decrease in mean on both samples and an increase in variance for the skilled sample and a decrease in variance for the unskilled sample; (ii) the mobility parameters show an increase in termination rate for the skilled and a decrease for the unskilled, a decrease in arrival rate of offers while unemployed on both samples and an increase of arrival rate of offers on the job for the unskilled sample. It is difficult to map these structural parameters to actual increase or decrease in mobility or to actual changes in inequality since individuals react to different environments by adjusting their reservation wage. For this reason, the next section will present counterfactual experiments evaluating the impact of mobility parameters and wage offer distribution parameters once agents adjust their behavior. We can however give an idea of the magnitude of the impact of the parameters on some observable variables. In Table 2, an arrival rate of offers while unemployed equal to 0.0965 means that skilled workers in 1995 should expect to receive a job offer within about 10 months. In Table 3 a termination rate of 0.0032 means that unskilled workers in 1995 should expect to be terminated in about 26 years. The combination of wage offer distribution and reservation wage estimates imply that the average *accepted* wage ranges from 10.71\$/h for unskilled workers in 1995 to 21.39\$/h for skilled workers in 1988.

The main conclusions we draw from the structural parameter estimates is that the differences across skills are substantial and the differences across years

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<sup>22</sup>For example, parameters estimates are in the same order of magnitude of Flinn (2002) (compare groups S3 and S4 in Table 4 with our skilled sample in 1988 and groups S1 and S2 with our unskilled sample in 1988), Flabbi (2009) (compare men in Table 2, specification (4) with our skilled sample in 1995) and Mabli (2008) (compare husbands in Table 4 and 5 with our 1995 sample). The main difference is in the arrival rates while unemployed that we estimate to be lower than previous literature.

are not dramatic but noticeable. We also judge the estimates to be relatively robust to the introduction of measurement errors. However, as it often the case, the estimated reservation wages in the specifications without measurement errors are very small, in particular for the unskilled sample. We have therefore chosen to use the measurement errors specification as our favorite specification to generate the experiments and compute the measures of inequality.

## 5.2 The fit of the model

Before moving to the implementation of policy experiments that may clarify these issues, we present some evidence about the ability of the model to fit the data. We only focus on accepted wages that immediately follow an unemployment spell and on hazard rates out of unemployment. We focus on these two features because they allow for a description of the raw data that imposes very little structure on them but we restrain from formal testing because of the small sample size.<sup>23</sup> In particular, the sample size for the skilled groups is extremely small and the non-parametric estimators we use to compare the model with the data extremely unreliable. Therefore, we expect a more conclusive comparison on the unskilled samples than on the skilled sample.

In Figure 1 we present the histogram of wages accepted immediately after an unemployment spell together with the density implied by the estimated model. The model fits quite well the empirical distributions of unskilled workers, in particular on 1996. The small sample of skilled workers generate quite irregular histograms that, however, the model seems to mimic reasonably well. The exception is a major mismatch on the low tail of the 1988 distribution. Our conclusion from this informal analysis is that overall the model is able to replicate the shape and location of accepted wages after a period of unemployment.

In Figure 2 we present the hazard rate out of unemployment implied by the model (the horizontal line) and an estimated hazard computed with the life table method (the dots). The life table method delivers a maximum likelihood estimate of the within-interval hazard computed under the assumption that the hazard is constant over the interval (Kalbfleisch and Prentice 2002.) We use an interval of one month. The structure imposed by our model is obviously quite strong since it implies a constant hazard. The empirical hazard estimated by the life table methods exhibits some variation but no significant duration dependence on the unskilled samples. The skilled sample, instead, shows positive duration dependence. However, the life table method requires a large number of observations for precise estimation while in our sample we only have 10 unemployment durations for each skilled sample in each year. We then conclude that the model implication of a constant hazard out of unemployment is not too restrictive on the unskilled data while no reliable evidence can be inferred from the skilled samples.

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<sup>23</sup>We only observe 9 wages after unemployment on the skilled 1988 sample and 7 on the skilled 1995 sample; we observe 50 of such wages on the unskilled 1988 sample and 51 on the unskilled 1995. Observed unemployment durations (complete and right censored) are: 10 on both skilled samples, 58 on the unskilled 1988 sample and 71 on the unskilled 1995 sample.

## 6 Policy Experiments

Given the estimated structural parameters it is possible to generate “counterfactual labor markets”, i.e. labor market characterized by different combinations of parameters. We use these counterfactual experiments to evaluate the contribution of specific parameters on observed outcomes taking into account equilibrium effects as summarized by changes in the reservation wage. Recall that a change in the reservation wage affects all the observables: the accepted wage distributions (since the truncation point changes) and the durations in the different states (since the probability to accept a new job changes.)

A straightforward way to implement counterfactual experiments is by simulation: we choose the appropriate combination of parameters, we compute the new equilibrium and we then extract wages and durations to create labor market careers. For each environment, we generate 10,000 labor market careers, all starting from the unemployment state. We follow individuals up to 10 shocks and for each shock we record accepted wages, durations in the state and total time in the labor market. We do not add measurement errors to the variables because we can actually observe the “true” values. More details about the implementation of the simulation exercise are in Appendix 8.3.

We present results on two experiments. In the first we fix all the parameters at the point estimates for 1995 except for the wage offers distribution parameters  $\mu$  and  $\sigma$  which we fix at the values estimated for 1988. This experiment, labelled *Distribution*, evaluates the impact of the change in the wage distribution on overall inequality and instability once the reservation wages are allowed to adjust. In the second, labelled *Mobility*, the wage distribution parameters are equal to the point estimates for 1995 but the mobility parameters  $\lambda_E$ ,  $\lambda_R$ ,  $\lambda_U$  and  $\eta$  are fixed to the values estimated for 1988. Analogously, this experiment computes the impact of changes in the exogenous components of mobility on inequality once individuals are allowed to adjust their behavior to the new environment.

For each experiment we provide a set of measures of earnings inequality and instability. The aim is to contrast differences between cross-sectional inequality, lifetime inequality and previous measures of instability presented in the literature. We compute four different sets of statistics. First, we compute standard cross-sectional wage inequality measures. Second, we compute the same inequality measures but on a longitudinal measure that takes into account the overall welfare of participating in each labor market. Third, we report descriptive statistics of labor market dynamics. Fourth, we compute a popular measure of earnings instability: the earnings volatility decomposition developed by Gottschalk and Moffitt (1994). Each of these measures is defined and presented in more details in the remaining of the section.

To measure inequality we use three indicators from the Generalized Entropy class of inequality indexes which is defined as in Shorrocks (1984):

$$GE(\zeta) = \frac{1}{\zeta(1-\zeta)} \left[ \frac{1}{n} \sum_{i=1}^n \left( \frac{y_i}{\bar{y}} \right)^\zeta - 1 \right]$$

where  $y_i$  is the variable of interest in a population of individuals  $i = 1, 2, \dots, n$ ;  $\bar{y}$  is the sample mean and  $\zeta$  is parameter. This class has some important properties that are useful for our exercise: (i) the sensitivity to the top of the distribution is governed by the parameter  $\zeta$ : the more positive the higher the sensitivity of the index to differences in the top of the distribution; (ii) each index can be additively decomposed in measures of within group and between group inequality; (iii) all indexes have a similar scale that makes comparisons easier. We report in Tables 4 and 5 three of the most popular indexes belonging to this class:  $GE(2)$  which equals half the square of the coefficient of variation,  $GE(1)$  which is the Theil entropy index, and  $GE(0)$  which is the mean log deviation.

We compute the indexes on a cross-section of the simulated data (top panel of Tables 4 and 5) and on the lifetime welfare of each individual (second panel). We define cross-section as a given “year” in our simulation where the year is defined by the time that has passed since the individual entered the labor market. We choose the period between 120 and 132 months (i.e. labor market careers in the 11th year) to give individuals enough time to enter the steady state portion of their labor market career.<sup>24</sup> The measure of lifetime welfare ( $LW$ ) is simply defined as the sum of the discounted values of the states that each individual occupies during her simulated labor market career<sup>25</sup>:

$$LW_i = \sum_{j=1}^{J-1} \exp(-\rho t_j) \int_{t_j}^{t_{j+1}} \xi_{ji} \exp(-\rho v) dv$$

where :

$$\xi_{ji} = \begin{cases} b & \text{if spell } j \text{ is unemployment} \\ w_{ij} & \text{if spell } j \text{ is employment} \end{cases}$$

Since we generate the simulation by starting with each individual in unemployment we do not include the first spell in computing the index to be closer to a steady state environment. Including the first spell means including a point in time that is a violation of the steady state since every individual is unemployed at time  $t_0 = 0$ .<sup>26</sup>

For comparison purposes, the first two columns of Tables 4 and 5 report the indexes computed on labor markets in which all the parameters are fixed at the estimated values for 1988 and for 1995. The last two columns report the proportion of the difference in the index between 1988 and 1995 that is “explained” by the experiment, i.e. they report the ratio:

$$(Index_{1995} - Index_{Experiment}) / (Index_{1995} - Index_{1988})$$

Results on the benchmark models confirm the increase in inequality both at the cross-sectional and lifetime level. The  $GE(2)$  index is increasing more, particularly for the skilled, confirming previous literature suggesting that the

<sup>24</sup> Any 12-month period above 60 months generates similar results.

<sup>25</sup> See for example Flinn (2002), Appendix B.

<sup>26</sup> Moreover, including the first spell makes the inequality measures very sensitive to a small number of outliers taking a lot of time to find their first job.

growth in wage inequality is concentrated at the top end of the wage distribution.<sup>27</sup> This is also consistent with the larger increase in inequality experienced by the skilled with respect to the unskilled. We also use the simulated data to decompose the total increase in cross-sectional and lifetime inequality in a between and a within skills component. We find the within component is becoming more important in explaining both cross-sectional and lifetime inequality as we move from 1988 to 1995.<sup>28</sup>

The main results on the experiments for the skilled sample are: changes in the wage distribution are able to fully account for the observed change in cross-sectional inequality and for up to 3/4 of the change in lifetime inequality. Changes in the exogenous component of mobility, instead, can only generate the increase in cross-sectional inequality. Had the distribution parameters stayed at their 1988 value, the coefficient of variation would have increased respectively to 0.045 and 0.052 instead of the actual 0.075.

A different pattern is produced by the sample of unskilled workers (Table 5). The distribution parameters have contributed negatively<sup>29</sup> to the growth of cross-sectional inequality but they explain about 2/3 of the increase in lifetime inequality. Changes in mobility parameters have a complementary impact: they explain the increase in cross-sectional inequality but they contribute negatively to the increase in lifetime inequality.

The main messages we draw from these first set of statistics are:

lifetime inequality and cross-sectional inequality increases have been generated by different sources;

the sources of increased inequality for skilled workers and unskilled workers are also different;

changes in the wage offer distribution are the main determinants of the increase in inequality for skilled workers while both mobility changes and wage offer distribution changes are needed to explain cross-sectional and lifetime inequality increases for the unskilled.

The wage offer distribution had to be a main determinant of the increase in both cross-sectional and lifetime inequality for the skilled sample because the

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<sup>27</sup>Lemieux (2006b) finds that the return to post-secondary education increased sharply while returns to lower levels of education remained relatively unchanged. Olivier Deschênes (2002) shows that (log) wages are an increasingly convex function of years of education. In other words, the wage gap between college post-graduates and college graduates has increased more than the wage gap between college graduates and high school graduates, which has itself increased more than the wage gap between high school graduates and high school dropouts. Looking at the distribution of taxable earnings, Piketty and Saez (2003) also find that relative wage gains are disproportionately concentrated in the very top of the earnings distribution.

<sup>28</sup>The proportion of overall cross-sectional variation explained by the within component increases from 68% in 1988 to 87% in 1995 and the proportion of overall lifetime variation from 83% in 1988 to 89% in 1995. This is not the main result of the literature, even if some contribution finds it: for instance, Lemieux (2006a) shows that within-group inequality grew substantially among college-educated workers but changed little for most other groups.

<sup>29</sup>Which means that had they stayed at their 1988 value, inequality would have been higher in 1996.



variance of the wage offer distribution is higher in 1995 than in 1988. Equilibrium effects, however, can magnify or reduce the impact of this change through their impact on the reservation wage. For example, the mean of the wage offer distribution decreases from 1988 to 1995, adding to the decrease in the reservation wage already implied by the increase in variance. The decrease in the reservation wage has a direct impact on the increase in cross-sectional inequality that together with the increase in variance imply that changes in the wage distribution can fully account for the increase in cross-sectional inequality. Lifetime inequality, instead, is also strongly affected by the exogenous mobility parameters. The changes in the arrival rate of offers parameters from 1988 to 1995 do not favor mobility (they both decrease) but the change in the termination rate does (it increases by about 60%). Again, the final impact depends on which effect dominates and on how the reservation wage changes. It turns out that if the mobility parameters are set to 1988 leaving the other parameters to 1995 the reservation wage increases: as a result the mobility experiment does not explain the increase in lifetime inequality, as somewhat expected, but explains a large portion of the cross-sectional inequality increase.

The main reason why we see these differential impacts on lifetime inequality and cross-sectional inequality on the unskilled sample are the different equilibrium effects. The *distribution* experiment means increasing both mean and variance of the wage offer distribution from their value in 1996: this is a favorable change for the worker who reacts by decreasing the reservation wage. As a result the spread on accepted wages must be higher. However, the higher variance in the wage offer distribution in a dynamic dimension means that individuals may move more quickly up the wage ladder reducing lifetime inequality. As a result we observe that the lower mean and variance of the wage offer distribution in 1995 with respect to 1988 can be the source of the increase in lifetime inequality but cannot be the source of the increase in cross-sectional inequality. The *mobility* experiment has exactly the opposite effect because the combined changes in mobility parameters actually imply an increase in the reservation wage to about 7.8 dollars from the benchmark level of about 5.15 dollars in 1996.

The differential impact of mobility parameters on cross-sectional and lifetime inequality confirms the methodological point of Flinn (2002): when comparing inequality between two structurally different environments, an explicit treatment of the dynamics involved may lead to quite different conclusions. For example, in Flinn (2002) the lower cross-sectional inequality of Italy with respect to the U.S. was masking a higher lifetime inequality. Here, the mobility experiment implies a decrease in cross-sectional inequality but an increase in lifetime inequality. As a result, changes in the exogenous mobility parameters can explain some of the increase in cross-sectional inequality between 1988 and 1996 but none of the increase in lifetime inequality.

We now look at the other measures of instability to check how they compare with these sets of results.

A vast descriptive literature uses measures such as median tenure or job separation rate to account for the evolution of job stability and job security

over time. Based on the evidence produced in this literature it is not clear if instability has increased over the late 1980's and 1990's.<sup>30</sup> We provide a very short list of similar measures on our generated data: the median duration of employment and unemployment spells and the mean number of jobs in the entire labor market career.

The results are reported in the third panel of Table 4 and 5. Looking at the statistics for the two benchmark cases, the overall picture is of increasing instability for the unskilled (lower median durations, higher number of jobs held) and of better employment conditions for the skilled (similar median employment duration but much shorter median unemployment duration). For the skilled we partially confirm what we have found: the changes in wage distribution explain the (minimal) changes in the employment variables. However, none of the two experiments is able to explain the change in median unemployment. The main reason is that the changes in median unemployment is strongly affected by the decrease in the  $\lambda_U$  parameter which we only change together with the other mobility parameters. A similar interpretation holds for the unskilled sample.

Finally, we parallel what is usually done on longitudinal data to isolate earnings instability from other permanent components (Gottschalk and Moffitt 1994 and 2002) by considering our simulated data as panel data on wages.

Following the literature, we consider wages  $w_{it}$  composed of an individual fixed effect  $\mu_i$  and a transitory shock  $v_{it}$ . The two components are orthogonal to each other and are allowed to vary over time with the respective loading factors  $\phi_t$  and  $\pi_t$ :

$$\log w_{it} = \phi_t \mu_i + \pi_t v_{it} \quad (14)$$

We denote with  $\log w_{it}$  the log of the simulated wage and we assume  $v_{it}$  is an AR(1) process:  $v_{it} = \rho v_{it-1} + \epsilon_{it}$  with  $\epsilon_{it} \rightsquigarrow iid(0, \sigma_\epsilon^2)$ .

We fit the sample covariance structure of log hourly wages to the covariance structure implied by model (14) using a minimum distance estimator. The results of this exercise are shown at the bottom of Tables 4 and 5 where we show the average of the total, transitory and permanent variance. Figures 3 and 4 show the transitory variance plotted against the first 20 years of labor market experience (240 months).

Consistent with the literature we find an increase in the total variance and in the transitory variance of wages between 1988 and 1996. The increase in the transitory variance is larger for the skilled and is larger than the increase in the permanent variance. The calculation of the transitory variance keeping the exogenous mobility rates fixed at the 1988 level shows that these parameters account for about 87% of the increase in the transitory variance on the skilled sample and for more than 100% of the increase within the unskilled. Keeping distribution parameters fixed at the 1988 level accounts for about 100% of the

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<sup>30</sup>See for example David A. Jaeger and Ann Huff Stevens; David Neumark et al. and Annette Bernhardt et al. in the special issue of The Journal of Labor Economics, Volume 17, October 1999.

increase in the transitory variance between the two periods for the skilled but contributes negatively for the unskilled.

Also consistent with the literature is the finding that the increase in the total and transitory variance of wages among the skilled is larger than among the unskilled. Figure 3 and 4 show that the transitory variance of wages among the skilled grew substantially over the two periods while it grew less among the unskilled. The same Figures show that mobility rates explain much of the increase of transitory variance among the unskilled and little among the skilled. Changes in distribution parameters significantly contributed to the growth of instability among unskilled workers while they do not explain much of the evolution of the transitory variance of wages among skilled workers.

These results confirm some of what we have found so far: skilled and unskilled have different sources of increased instability; changes in the wage distributions fully explain the changes for the skilled. However, we do not find differences in the sources of increased transitory and permanent volatility and we find a huge effects of the exogenous mobility parameters on the unskilled sample.

## 7 Conclusion

Many contributions suggest that earnings inequality and instability have increased during the 1980s and 1990s. This paper develops and estimates an on-the-job search model of the labor market to study the contribution of wage offers inequality and labor market dynamic in explaining these changes and to contrast the evolution of cross-sectional inequality with that of lifetime inequality. We extract two estimation samples (late 1980s and late 1990s) from the Calendar Section of the PSID. Also based on descriptive statistics from these data we add a non-standard feature to our on-the-job search model: a reallocation shock able to generate the significant proportion of job-to-job transitions followed by a wage decrease that we observe in the data. This feature also allows us to compare two specifications one without and one with measurement errors in wages.

We obtain maximum likelihood estimates by skill levels where we define the skilled group as individuals who have completed at least some years of College. The main differences between the structural parameters of the two periods are as follows. The wage offer distribution experiences a decrease in mean on both samples, an increase in variance for the skilled sample and a decrease for the unskilled sample. The mobility parameters show an increase in termination rate for the skilled and a decrease for the unskilled, a decrease in arrival rate of offers while unemployed on both samples and an increase of arrival rate of offers on the job for the unskilled sample. These results are robust to the presence of measurement errors in the specification.

Using the point estimates of the structural model we generate counterfactual experiments by simulations, that is we generate simulated labor market histories mixing different combinations of parameters from the two periods. The objec-

tive is to isolate the contribution of some parameters of interest to the increase in earnings instability taking into account equilibrium effects as summarized by changes in the reservation wages. We use four metrics to evaluate earnings inequality and instability: cross-sectional inequality; lifetime inequality; durations and transitions statistics; and the Gottschalk and Moffitt (1994) volatility decomposition. We find that lifetime inequality and cross-sectional inequality increases have been generated by different sources and that these sources are different by skills. Changes in the wage offer distribution are the main determinant of the increase in inequality for skilled workers while both mobility changes and wage offer distribution changes are needed to explain the increase in cross-sectional and lifetime inequality for the unskilled. We also find that the within skill component is more important than the between skills component in explaining both cross-sectional and lifetime inequality and more so as we move from 1988 to 1995.

This evidence is consistent with the literature that emphasizes different explanations for the rise of wage inequality at different points of the distribution. Among the possible explanations some literature favors the institutional explanation for the bottom part of the distribution (the fall of the value of the minimum wage or the decline of the unions) and the technological explanation for the top part (skill biased technical change or polarization of the labor market). While neither the institutional nor the technological explanation can be directly linked to our parameters, we think that the skill biased technical change explanation is consistent with the fact that we estimate the increase in the variance of the wage offer distribution only for the skilled but not for the unskilled.

We find two main limitations in our work: removing them may constitute a promising venue for future research. First, we assume stationarity but we estimate that some crucial parameters are different between the two periods. Removing stationarity is then an important step in obtaining a more appropriate description of labor markets evolving over time. While a well-developed theoretical literature is present, empirical applications able to estimate non-stationary models are rare. Bowlus and Robin (2004) is a very interesting example but an estimable search model that could incorporate at least some crucial non-stationary features is still lacking. Second, our contribution does not specifically model and study the role of mobility across occupations and industries. Interesting and recent work that addresses this issue in relation to inequality is present in the literature, for example Kambourov and Manovskii (2008a and 2008b). However, embedding this additional dynamic in an estimable search model that could provide a description of the evolution of lifetime inequality has so far proved to be extremely difficult.<sup>31</sup>

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<sup>31</sup>A major contribution is Bagger, Fontaine, Postel-Vinay and Robin (2006) that allows for the separate identification and estimation of the contribution of human capital accumulation over the life cycle within a job search model. This is a step in the direction we argue since the accumulation of job-specific human capital is crucial to understand the link between wage inequality and occupational mobility.

## 8 Appendix

### 8.1 Data Appendix

We construct the individual job and unemployment spells in the two observation windows 1988-1990 and 1995-1997 as follows. Consider the window 1988-1990 (the window 1995-1997 is treated in the same way.) The calendar information on monthly labor market status of surveys 1988-1990 refers to the months from January 1987 to December 1989 i.e. employed individuals at the date of the interview are asked to report which months of the previous year they were holding the current job, they are also asked whether they changed job in the previous year and which months of the previous year they were holding the other job. Unemployed individuals at the date of the interview are asked which month of the previous year they were employed in their last job. We start by selecting employed and unemployed heads at the date of the first interview (e.g. March 1987).

Both employment and unemployment durations could be potentially left-censored but the PSID contains some retrospective information both for employed and unemployed individuals that solves the issue. At the time of the interview employed individuals are asked the tenure in months in their current job (variable V14167 in 1987 survey) and unemployed individuals are asked for how many weeks they have been looking for a job (variable V14242 in 1987 survey). We use this information to build an employment tenure also for the first job spell sampled in the calendar and an unemployment duration for those whose first sampled spell is unemployment.

For employed individuals at the time of the first interview, we sum the retrospective information on tenure in the current job at the date of the interview to the information on the number of months in the current job (following the date of the interview) obtained from the calendar. The resulting duration is the tenure on the first job spell sampled ( $t_1(i)$ ). Each employed person in 1987 is then followed through his subsequent job changes (if any) with the respective durations ( $t_2(i)$  and  $t_3(i)$ ) calculated on the basis of the calendar information until either he falls in unemployment or the last job spell in the observation window is right censored. Moreover, since only very few individuals experience more than three job-to-job transitions over our period of observation and since the computational burden greatly increases with the number of transitions<sup>32</sup> we have decided to use information on at most three consecutive job spells. An indicator variable ( $r_k(i) = 1$ ) indicates the transition from employment to unemployment and another indicator variable ( $c_k(i) = 1$ ) indicates right censoring. We limit ourselves to only one cycle per individual. A cycle is defined as a spell that starts and ends in the unemployment state since the unemployment state “resets” the dynamic process. We limit ourselves to one cycle because, given the short period under consideration of three years, the number of those that start in employment, fall in unemployment and find another job with a

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<sup>32</sup>This is due to the many different likelihood combinations that are generated as the number of transitions considered increases. See section 4.1 for a detailed explanation.

valid wage after the unemployment spell is of only 9 individuals in the 1987-1989 window and 5 in the 1995-1997 window. On top of that all additional observations are right censored limiting their identification power.

For unemployed individuals at the time of the first interview, we sum the retrospective information on the number of weeks of job search at the date of the interview (turned into 4.3 weeks= 1 month) to the number of months spent in unemployment after the interview obtained from the calendar section. The resulting sum is the unemployment duration ( $t_u(i)$ ). Each unemployed person is then followed until he finds a job and through the subsequent job changes whose durations are calculated on the basis of the monthly calendar information. Few unemployment spells which started in 1987 are still in progress at the time of the last interview, in this case the right-censoring indicator variable is defined as  $c_u(i) = 1$ .

The starting wage information is collected by PSID every time an individual starts a job during the calendar section period, including individuals that transit in the unemployment state. Therefore, for all the individuals that we first observe as unemployed and that find a job within our window of observation we can record the starting wage of the job accepted immediately after the unemployment spell. Within the calendar section period, any time an individual engages in a job-to-job transition, the PSID records the ending wage in the job just left and the starting wage in the new job just accepted. For example, if a worker leaves the job in which we are first observing him and moves to a new job, the ending wage will be recorded in our data set as  $w_1(i)$  and the starting wage in the new job as  $w_2(i)$ .

In principle the PSID will record two wages for each job spell  $k$  but only for those who change two jobs within the window: for somebody transiting from job 1 to job 2, we have a starting wage for job 2 and an ending wage for job 1, and then at the transition from job 2 to job 3, we have an ending wage for job 2 and a starting wage for job 3. Notice that for those who transit from job 1 to job 2 but then fall into unemployment and never reappear, we only have the starting wage of job 2 and no ending wage. Given that we have chosen to have one single wage for each job spell, we have to choose which one to keep (starting or ending wage) for those who report both. We have chosen to always keep the ending wage except in those few cases in which the ending wage is missing.<sup>33</sup>

This leads to the following process from the raw data to the estimation sample. Over the 1987-1989 window the raw data record 2737 employed male head

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<sup>33</sup>This pragmatic solution makes the extraction of the estimation sample and the specification of the likelihood much easier without distorting the data in any significant way because the number of individuals in this situation turns out to be relatively small and for the majority of them the starting and ending wage are quite similar. The number of individuals who could potentially report two wages on the 1988 sample is 91. Out of these, 10 reported only the starting wage and 29 only the ending wage, 52 reported both. For these 52 individuals the median difference between the starting wage and the ending wage is 81 cents over a mean  $w_2$  of 15.4\$ an hour. The corresponding figures for the 36 individuals with a positive  $w_3$  in the 1995 sample are: 3 reported only the starting wage, 7 only the ending wage and 26 reported both. For these the median difference between the starting wage and the ending wage is 60 cents over a mean  $w_2$  of 11.6\$ an hour.

of households at the interview date in 1988. Out of these, 829 change job at least once during the period and 602 report a valid wage information. In the window 1994-1996 we start with 2913 employed male heads: 790 change job at least once and 467 report a valid wage information. To these we add 70 individuals unemployed at the date of the interview and with valid wage information over the 1987-1989 period and 86 unemployed with valid wage information over the 1995-1997 period. Once divided in skilled workers and unskilled workers and trimmed of the top and bottom 1% conditional on the skill level, these samples correspond to the data reported in Table 1.

## 8.2 Recovering $(b, \rho)$

As common in the literature, we assume a fixed value for the discount rate:  $\rho = 0.05$ . Given MLE estimate of the other structural parameters, it is possible to recover  $b$  in the following way. By imposing

$$U = W(w^*)$$

we get:

$$\begin{aligned} U &= \frac{w^* + [\eta + \lambda_R G(w^*)] U + \lambda_E \int_{w^*} W(w') dG(w') + \lambda_R \int_{w^*} W(w') dG(w')}{\rho + \lambda_E \tilde{G}(w^*) + \lambda_R + \eta} \\ U &= \frac{w^* + (\lambda_E + \lambda_R) \int_{w^*} W(w') dG(w')}{\rho + (\lambda_E + \lambda_R) \tilde{G}(w^*)} \end{aligned} \quad (15)$$

which has the relevant property in this context of not being a function of  $b$ . We can then plug it in (3) to obtain the following:

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

which is an integral equation independent from  $b$  that we can solve for  $W(w)$ . We can now go back to (4) and, using the estimated structural parameters, the estimated reservation wage, the assumed discount rate and the previous solution for  $W(w)$ , recover  $b$  as:

$$b = \frac{\rho + \lambda_U \tilde{G}(w^*)}{\rho + (\lambda_E + \lambda_R) \tilde{G}(w^*)} \left[ w^* + (\lambda_E + \lambda_R) \int_{w^*} W(w') dG(w') \right] - \lambda_U \int_{w^*} W(w') dG(w') \quad (16)$$

Notice that by continuity we can apply the invariance property of the MLE estimator and therefore the estimator of  $b$  obtained in this way is the MLE estimator.

### 8.3 Details of the simulation exercise

Each of the 10,000 labor market histories starts in the unemployment state. The data are then generated following this procedure:

1. one unemployment duration is drawn from the exponential density (6);
2. one acceptable wage is drawn from the appropriate wage density in (8);
3. one employment duration is drawn from the exponential density (7);
4. one uniform random variable is drawn to determine the type of shock to the employed individual (job offer, reallocation, termination) taking into account the respective probabilities of each shock type:
  - (a) if an on-the-job job offer shock hits the worker, an acceptable wage is drawn from the appropriate wage density in (8);
    - i. the process is then iterated from step 2 starting at the new wage.
  - (b) if a reallocation shock hits the worker, an acceptable wage is drawn from the appropriate wage density in (8);
    - i. the process is then iterated from step 2 starting at the new wage.
  - (c) if it a termination shock hits the worker, the process is reset and the procedure restarts from step 1.

The process is iterated until each worker has received 10 shocks. For each labor market history we record durations in each states, accepted wages and total time in the labor market. Notice that the time spent in the labor market is not the same for all the individuals so when we give statistics on durations we use relative measures. The average span of labor market career generated is about 20 years (232 months in the benchmark case for 1988 and 244 months in the benchmark case for 1995).



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**Table 1: Descriptive Statistics**

	Skilled				Unskilled			
	1988		1995		1988		1995	
Wages (\$/h):	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
$w_u$	17.68	11.49	18.11	10.88	10.51	10.08	12.88	19.22
$w_2$	21.34	7.09	18.08	7.12	13.22	6.84	11.60	6.44
$w_3$	21.44	7.42	18.63	6.42	13.62	7.14	11.08	4.32
Two job spells in cyle:								
number	86		71		235		260	
with larger w2	0.58		0.65		0.47		0.47	
Three job spells in cyle:								
number	33		5		53		29	
with larger w3	0.70		0.60		0.55		0.55	
Durations (months):	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
$t_u$	9.00	10.41	7.70	5.50	11.87	11.93	15.18	15.09
right censored	0.10		0.30		0.17		0.28	
$t_1$	48.45	54.78	53.66	58.64	49.16	60.95	48.97	65.65
right censored	0.33		0.18		0.34		0.17	
$t_2$	14.76	9.45	14.73	9.42	13.46	9.75	14.70	10.03
right censored	0.59		0.87		0.66		0.79	
Number of obs.	146		106		495		382	

Notes: Sample extracted from the Calendar Section of the PSID. 1988 defines a window of observation covering survey years 1988-1990; 1995 covers survey years 1995-1997. Employment and unemployment durations are in months and wages are hourly deflated with base January 2000. Skilled = more than 15 years of education; Unskilled = equal or less than 15 years of education.

**Table 2: Maximum Likelihood Estimates - Skilled**

	No Measurement Errors		Measurement Errors	
	1988	1995	1988	1995
$\lambda_U$	0.1046 ( 0.0350 )	0.1035 ( 0.0399 )	0.1016 ( 0.0344 )	0.0965 ( 0.0399 )
$\lambda_E$	0.0204 ( 0.0044 )	0.0223 ( 0.0055 )	0.0407 ( 0.0112 )	0.0350 ( 0.0123 )
$\lambda_R$	0.0081 ( 0.0012 )	0.0058 ( 0.0011 )	0.0000 ( 0.0000 )	0.0000 ( 0.0000 )
$\eta$	0.0012 ( 0.0005 )	0.0019 ( 0.0008 )	0.0016 ( 0.0004 )	0.0026 ( 0.0006 )
$\mu$	2.7578 ( 0.0627 )	2.4637 ( 0.1190 )	3.0037 ( 0.1196 )	2.6675 ( 0.1930 )
$\sigma$	0.4570 ( 0.0389 )	0.5709 ( 0.0661 )	0.3182 ( 0.0692 )	0.4391 ( 0.0930 )
$w^*$	7.2361	6.0373	10.1684 ( 3.2274 )	7.2119 ( 2.5784 )
$\mu_\varepsilon$			-0.0908 ( 0.0153 )	-0.0535 ( 0.0116 )
$E(w)$	17.5007 ( 0.9371 )	13.8276 ( 1.2752 )	21.2060 ( 2.1921 )	15.8625 ( 2.5157 )
$V(w)$	71.1405 ( 12.5506 )	73.6841 ( 15.8977 )	47.9175 ( 16.6940 )	53.5181 ( 15.1045 )
Loglik	-1158.80	-871.53	-1189.64	-876.01
N	146	106	146	106

Notes: Asymptotic standard errors in parentheses.

**Table 3: Maximum Likelihood Estimates - Unskilled**

	No Measurement Errors		Measurement Errors	
	1988	1995	1988	1995
$\lambda_U$	0.0704 ( 0.0100 )	0.0483 ( 0.0068 )	0.0765 ( 0.0150 )	0.0591 ( 0.0200 )
$\lambda_E$	0.0088 ( 0.0017 )	0.0131 ( 0.0023 )	0.0415 ( 0.0113 )	0.0667 ( 0.0291 )
$\lambda_R$	0.0079 ( 0.0006 )	0.0094 ( 0.0008 )	0.0000 ( 0.0000 )	0.0000 ( 0.0000 )
$\eta$	0.0041 ( 0.0004 )	0.0030 ( 0.0004 )	0.0041 ( 0.0004 )	0.0032 ( 0.0004 )
$\mu$	2.1973 ( 0.0370 )	2.0647 ( 0.0428 )	2.3754 ( 0.1507 )	2.0928 ( 0.2671 )
$\sigma$	0.5751 ( 0.0236 )	0.5979 ( 0.0271 )	0.4596 ( 0.0699 )	0.5368 ( 0.1023 )
$w^*$	1.7639	2.3381	5.6810 ( 1.1117 )	5.1525 ( 0.8245 )
$\mu_\varepsilon$			-0.1563 ( 0.0163 )	-0.1373 ( 0.0140 )
$E(w)$	10.6195 ( 0.3686 )	9.4262 ( 0.3492 )	11.9530 ( 1.3885 )	9.3643 ( 1.9075 )
$V(w)$	44.1992 ( 5.3050 )	38.1902 ( 4.6115 )	33.5978 ( 4.4459 )	29.2839 ( 3.0857 )
Loglik	-3644.07	-3410.95	-3680.63	-3439.71
N	495	382	495	382

Notes: Asymptotic standard errors in parentheses.



**Table 4: Policy Experiments - Skilled**

	Benchmarks:		Policy Experiments:			
			Index Values		Proportion of 1995-1988 Differential Explained	
	1988	1995	Distribution	Mobility	Distribution	Mobility
Cross-sectional inequality measures: earnings						
$GE(2)$	0.045	0.075	0.045	0.052	1.003	0.745
$GE(1)$	0.043	0.068	0.042	0.048	1.042	0.804
$GE(0)$	0.044	0.067	0.042	0.046	1.070	0.888
Lifetime inequality measures: welfare						
$GE(2)$	0.104	0.154	0.116	0.177	0.772	-0.459
$GE(1)$	0.106	0.147	0.119	0.177	0.683	-0.725
$GE(0)$	0.124	0.172	0.146	0.233	0.551	-1.272
Labor market dynamic measures:						
Median[ $t_e$ ]	0.249	0.250	0.249	0.251	1.000	-1.000
Median[ $t_u$ ]	0.098	0.024	0.023	0.024	-0.014	0.000
Av. n. jobs	7.302	6.975	7.000	6.950	0.076	-0.076
Gottschalk-Moffitt earnings volatility decomposition:						
Total	0.104	0.175	0.104	0.113	1.000	0.873
Transitory	0.093	0.156	0.093	0.101	1.000	0.873
Permanent	0.011	0.019	0.010	0.012	1.098	0.854

Notes: The experiments use the estimates from the measurement error specification. *Distribution* experiment: all the parameters are fixed to 1995 point estimates except  $(\mu, \sigma)$  which are fixed to 1988 point estimates. *Mobility* experiment: all the parameters are fixed to 1995 point estimates except  $(\lambda_E, \lambda_R, \lambda_U, \eta)$  which are fixed to 1988 point estimates. The reported measures of inequality belongs to the Generalized Entropy class  $GE(\zeta)$  where the higher the  $\zeta$  parameter the higher is the sensitivity to differences at the top of the distribution:  $GE(2)$  = half the square of the coefficient of variation;  $GE(1)$  = Theil entropy index;  $GE(0)$  = mean log deviation.

**Table 5: Policy Experiments - Unskilled**

	Benchmarks:		Policy Experiments:			
			Index Values		Proportion of 1995-1988 Differential Explained	
	1988	1995	Distribution	Mobility	Distribution	Mobility
Cross-sectional inequality measures: earnings						
$GE(2)$	0.079	0.100	0.101	0.091	-0.045	0.433
$GE(1)$	0.073	0.089	0.092	0.073	-0.222	1.001
$GE(0)$	0.073	0.086	0.094	0.065	-0.568	1.618
Lifetime inequality measures: welfare						
$GE(2)$	0.200	0.296	0.232	0.324	0.669	-0.291
$GE(1)$	0.191	0.279	0.224	0.313	0.617	-0.388
$GE(0)$	0.237	0.392	0.299	0.477	0.598	-0.543
Labor market dynamic measures:						
Median[ $t_e$ ]	0.231	0.202	0.202	0.226	0.000	0.828
Median[ $t_u$ ]	0.109	0.058	0.051	0.056	-0.137	-0.039
Av. n. jobs	6.810	7.040	7.220	6.260	-0.783	3.391
Gottschalk-Moffitt earnings volatility decomposition:						
Total	0.183	0.206	0.221	0.132	-0.652	3.217
Transitory	0.162	0.184	0.198	0.115	-0.636	3.136
Permanent	0.020	0.022	0.023	0.017	-0.500	2.500

Notes: The experiments use the estimates from the measurement error specification. *Distribution* experiment: all the parameters are fixed to 1995 point estimates except  $(\mu, \sigma)$  which are fixed to 1988 point estimates. *Mobility* experiment: all the parameters are fixed to 1995 point estimates except  $(\lambda_E, \lambda_R, \lambda_U, \eta)$  which are fixed to 1988 point estimates. The reported measures of inequality belongs to the Generalized Entropy class  $GE(\zeta)$  where the higher the  $\zeta$  parameter the higher is the sensitivity to differences at the top of the distribution:  $GE(2)$  = half the square of the coefficient of variation;  $GE(1)$  = Theil entropy index;  $GE(0)$  = mean log deviation.

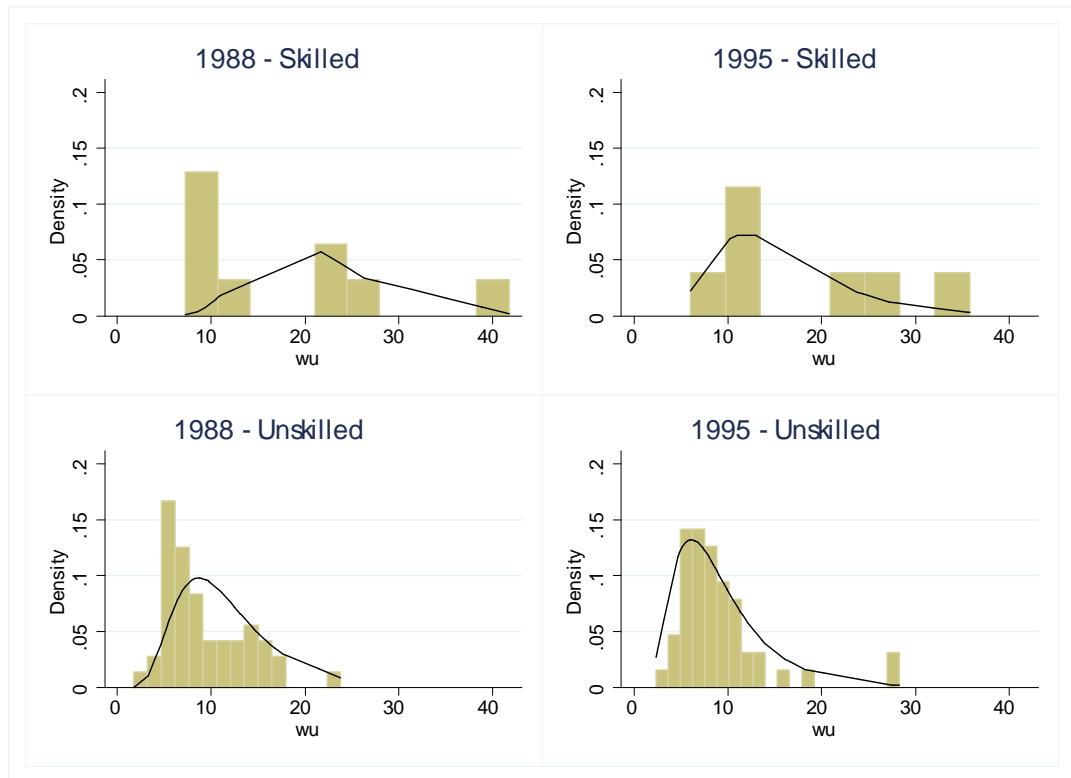


Figure 1: **Fit of the model on first wage after unemployment ( $w_u$ ).**

Note: Continuous lines are the predicted densities of the estimated model. Histograms are built on the data used in estimation.

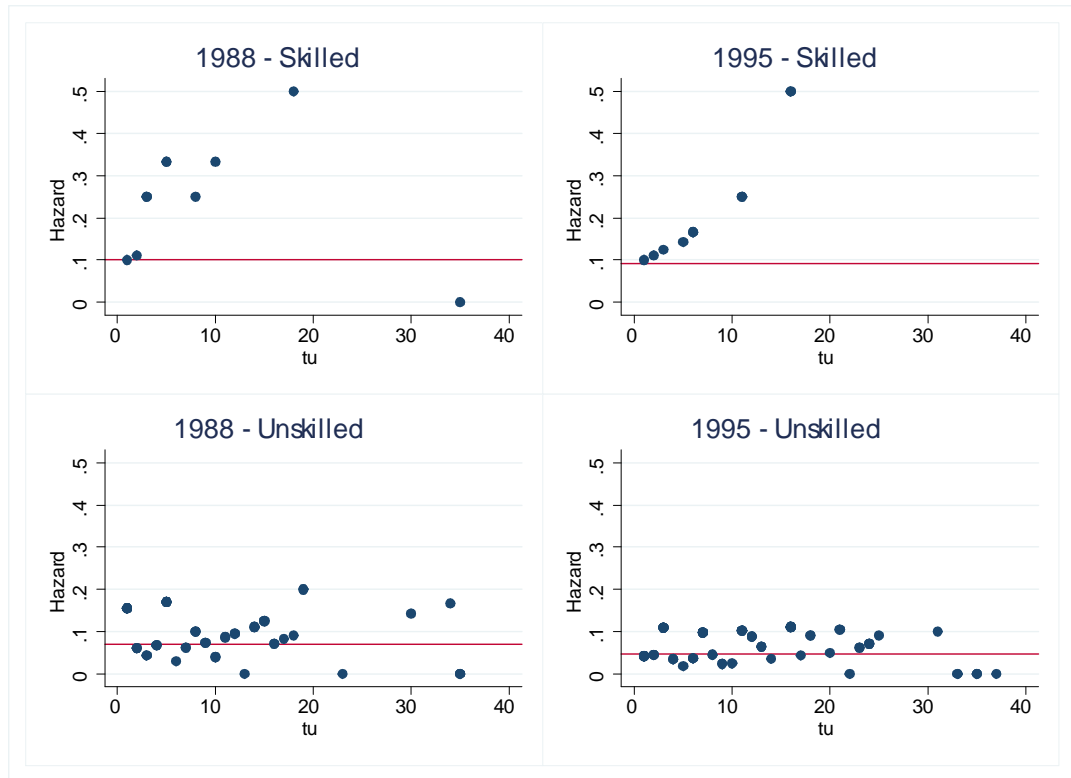


Figure 2: **Fit of the model on unemployment durations ( $t_u$ ).**

Note: Horizontal line is the hazard rate out of unemployment implied by the estimated model; dots are the empirical hazard out of unemployment estimated with the life table method.

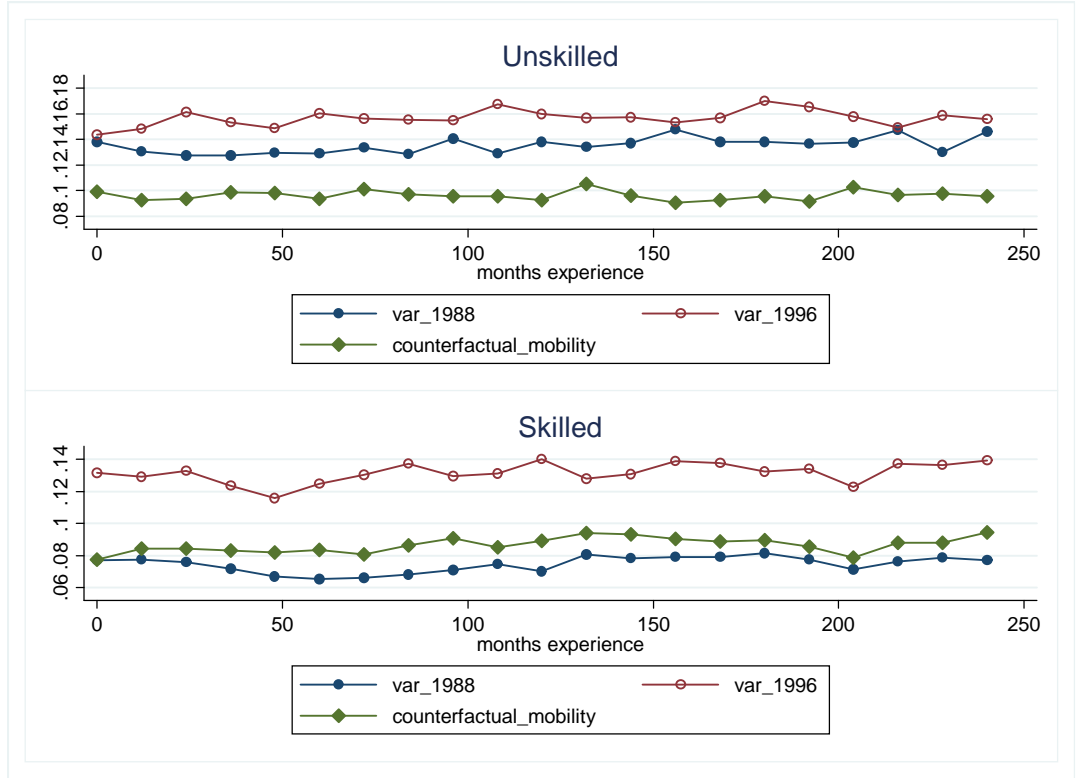


Figure 3: Transitory variance of wages of skilled and unskilled workers calculated on the 1988 and 1996 samples and on the counterfactual samples generated keeping mobility rates  $\lambda_E$ ,  $\lambda_E, \lambda_E, \eta$  fixed at their 1988 level.

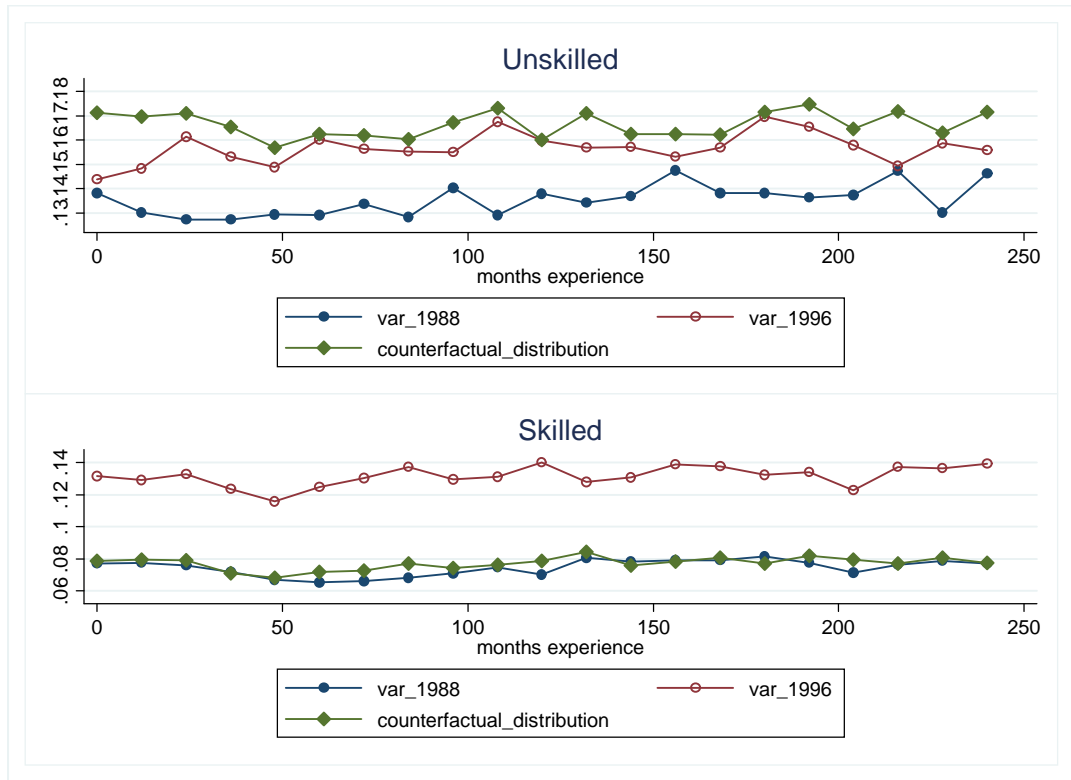


Figure 4: Transitory variance of wages of skilled and unskilled workers calculated on the 1988 and 1996 samples and on the counterfactual samples generated keeping distribution parameters  $E(w)$  and  $V(w)$  fixed at their 1988 level.