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ABSTRACT

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Many contributions suggest that earnings instability has 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 inequality and job mobility in explaining earnings instability. To study the evolution over time of these different components we extract two estimation samples (late 1980s and late1990s) from the Calendar Section of the PSID. We find that the main differences in the structure of the labor market between the two periods are in the job-to-job mobility and in the variance of the wage offer distributions: they both increase in the late 1990s. By generating counterfactual experiments, we also show that they both significantly contribute to the increase in earnings instability even if it is only their joint effect that generates what we observe in the data. Finally, we show that significant composition effects are at work since the behavior of skilled workers and unskilled workers are very different with respect to the above-mentioned labor market dynamics.

JEL Classification: J21, J31

Keywords: earnings instability, on-the-job search, structural estimation

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1   Introduction

Since the early 1970s the labor market in the United States has seen a substantial increase in wage dispersion. The literature on wage inequality has documented this fact using both cross-sectional and panel data methods which focus on individual-level data. An important manifestation of earnings inequality at the individual level is earnings *instability* i.e. the increasing variance of the transitory component of individual earnings. Gottschalk and Moffitt (1994) were the first to analyze the growth of earnings instability arguing that the increase in the variance of the transitory component of earnings has been an important contributor to the rise in overall earnings inequality.[1]

While the evolution of earnings instability in the US is relatively well established, less is known about the causes of the increase in instability. Some contributions propose the hypothesis of ex-ante differences in workers' abilities attributing the increase in wage inequality between the 1970s and the 1990s to the increasing returns to unobserved individual abilities.[2] However an increase in the variance of individual abilities should manifest itself in the increase in the dispersion of the persistent component of wages and not also in the transitory components.

Other scholars have described the 1980s as a period of increased economic "turbulence" characterized by a high rate of skill depreciation upon a job switch.[3] Increasing workers mobility (job-to-job and in and out of unemployment) is another possible cause of increasing earnings volatility, in particular when it leads to a decline in job security and job stability. However, identifying this decline in the data, or finding other evidence of the increased turbulence, has proved elusive. In particular, the empirical literature has not found a substantial increase in job (employer) mobility in the U.S. over the last three decades.[4]

Establishing a relationship between job mobility and the increasing variance of wages is also made difficult by the lack of direct measures of on-the-job search behavior. For example survey questions on job search behavior starts in the *Current Population Survey* (CPS) only in 1996 making impossible a comparison over the relevant decades. Moreover the absence of direct evidence on a reduction in average or median employment tenure is not sufficient to rule out an increase in mobility. The observed employment and wage outcomes reflect the interaction of several factors, including agents' reactions to different labor market conditions: the same duration in employment may result from a lack of better outside option for the worker or from a lower meeting rate with

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[1] More recent literature indicates an equal increase in the variance of the permanent and transitory components of earnings (Gottschalk and Moffitt, 2002; Katz and Autor, 1999). Contributions that have looked at different countries modelling the persistent and transitory components of earnings include Baker and Solon (2003) for Canada, and Dickens (2000) for the UK.

[2] For example Caselli (1999), Lloyd-Ellis (1999), and Galor and Moav (2000).

[3] For example Violante (2002), Ljungqvist and Sargent (1998) and Bertola and Ichino (1995).

[4] See for example Jaeger and Stevens (1999), Gottschalk and Moffitt (1999) and other contributions in the same *Journal of Labor Economics* special issue.

firms.

We develop an on-the-job search model of the labor market to estimate the separate effects of two components potentially responsible for the increase in earnings instability: an underlying (possibly demand-driven) wage offers distribution and a set of shocks that directly affect the chance to move between labor market states. In this framework we can actually compute, given an employment duration, which portion is due to the lack of better outside options for the worker and which portion is due to a lower termination rate. 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. For this reason, after estimating the model we will replicate the standard empirical analysis presented in the literature on simulated data from "counterfactual labor markets" to quantitatively assess which structural components of the labor market are mainly responsible for the increase in earnings volatility.

Our contribution is also related to the literature on occupational and industry mobility since we are able to give some foundation to why job mobility occurs.[5] We are not able to account for detailed heterogeneity but we are able to identify three sources of mobility out of a given job: better employment opportunities in another job (essentially an higher wage); an exogenous termination of the employment relationship; and a *reallocation* shock, particularly important to capture the "turbulence" in the labor market that is seen by some authors as an important determinant of the increased earnings instability. We formalize this shock following Jolivet, Postel-Vinay and Robin (2006).

Finally, from a methodological standpoint our paper is related to contributions that integrate labor market dynamic in an estimable framework departing from both descriptive empirical works (which leave little room to incorporate behavior) and more theoretically oriented contributions (which provide interesting equilibrium effects but no credible way to estimate their magnitude). Search models are one of the prominent framework to undergo this type of work and among recent contributions we are more closely related to Flinn (2002) and Jolivet, Postel-Vinay and Robin (2006): they both show the empirical content of on-the-job search models by assessing the determinants of labor mobility and wage dispersions. Flinn (2002) is closer to our paper in terms of the actual model developed and the identification and estimation strategy implemented while Jolivet, Postel-Vinay and Robin (2006) is closer in terms of the topic covered.

The estimation sample is extracted from the *Calendar Section* of the *Panel*

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[5] Moscarini and Thomsson (2008) document the behavior of occupational mobility at the three-digit level in the U.S. using CPS data over the 1976-2006 period. More specifically, Kambourov and Manovskii (2008a and 2008b) suggest that an observable increase in occupational mobility over the period may serve as a manifestation of the increased turbulence. They document that successive cohorts entering the labor market over the period are characterized by successively higher fractions of workers switching occupations (e.g. cook, accountant, chemical engineer) at all stages of their life-cycle and argued that changes in occupational mobility over time are intimately related to changes in the wage dispersion within age-education groups.

Study of Income Dynamics (PSID) which is the only section of the PSID that includes a credible description of job-to-job transitions. We generate two estimation samples: one at the beginning of the calendar section (survey years 1988-1990) and one at the end of the period over which the calendar section was collected (survey years 1995-1997).

The estimation results point to two main differences in the structural parameters governing labor mobility and wage dispersion over the two periods: an increase in the variance of the wage offer distribution and an increase in the on-the-job arrival rate of offers. Both components have the potential to fully explain the increase in earnings instability. By simulating counterfactual experiments we are able to quantify that none of the two changes is able to explain alone the increase in earnings instability when equilibrium effects are taken into account. On the overall sample they have a similar magnitude. However, this conclusion masks significant composition effects: when we take into account standard observed heterogeneity - we simply divide the sample in skilled and unskilled workers based on years of schooling completed - the behavior of the two groups is significantly different. Somewhat consistently with the literature on skill-biased technological change, the increase in the variance of the wage offers distribution has taken place only for skilled workers while unskilled workers experience an actual decrease in the variance of wage offers and a general deterioration of job mobility possibilities.

The paper proceeds as follows: section 2 presents the model, section 3 describes the data, section 4 discusses the identification and estimation of the model, section 5 and 6 presents 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.[6] Within the class of search model it is a model that has proved to be quite good in 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 offers distribution.

2.1 Environment

We work in continuos time within a stationary environment. Agents are infinitely lived, discount utility at the rate ρ 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

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[6] 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).

meet wage offers following a Poisson process with rate λ_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 λ_E sampled from the same probability distribution $G(w)$. However they may also receive the conventional job destruction shock with Poisson rate η or receive a *reallocation* shock (Jolivet, Postel-Vinay and Robin, 2006) with Poisson rate λ_R.

The presence of a reallocation shock is the only non-standard feature of our model. This is a shock that forces the worker to leave the current job without necessarily transit to the unemployment state. Formally, she is forced to leave the current job but has the possibility to draw a new wage offer that she may or may not accept. The idea is to capture situations in which firms restructuring include outplacement programmes for fired workers or 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. However, the frequency and credibility of these events in our data make us favor an explicit modelling that can be taken into account when we build counterfactual experiments. In other words, we prefer to interpret these transitions as potentially relevant elements of actual job instability and not as measurement errors in the data.

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 stationary 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:

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

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:

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

4

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:

$$\left(\rho + \lambda_E \widetilde{G}(w) + \lambda_R + \eta\right) W(w) = w + [\eta + \lambda_R G(w^*)] U \tag{3}$$
$$+ \lambda_E \int_w W(w')\, dG(w')$$
$$+ \lambda_R \int_{w^*} W(w')\, dG(w')$$

and:

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

The reservation values are then obtained by solving:

$$w^* \quad : \quad W(w^*) = U$$
$$w \quad : \quad W(w) = W'(w)$$

leading to:

$$w^* = \left[\rho + (\lambda_E + \lambda_R) \widetilde{G}(w^*)\right] U - (\lambda_E + \lambda_R) \int_{w^*} W(w')\, dG(w') \tag{5}$$
$$= \gamma(w^*) b + [\gamma(w^*) \lambda_U - \lambda_E - \lambda_R] \int_{w^*} W(w')\, dG(w')$$

$$where \quad :$$
$$\gamma(w^*) = \frac{\rho + (\lambda_E + \lambda_R) \widetilde{G}(w^*)}{\rho + \lambda_U \widetilde{G}(w^*)}$$

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:

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

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 the on-the-job search model developed in the paper we need at least 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 really 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 insta- bility over time (Gottshalk and Moffitt, 2002; Jaeger and Stevens, 1999). Since there are many issues of consistency of the job tenure and earnings variables over time, we focus on a special section (henceforth called *calendar section*) collected in the PSID between the years 1988 and 1997. In the calendar section individ- uals 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 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 since we need at least three years of data to obtain a dataset with sufficient numerosity, 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).[7] 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.

In terms of notation, the vector of variables on an individual i is defined as

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[7] It is worth mentioning that the years between 1988 and 1990 and between 1995 and 1997 are at similar points in the business cycle.

follows

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

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

3.1 Durations information

The PSID interviews heads of household in a period between February and August of each year. The calendar section of the PSID asks individuals 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 and unemployment durations for each individual.

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 and unemployed individuals are asked for how many weeks they have been looking for a job. 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 in January 1987 is unemployment.

The exact method to construct the individual job and unemployment spells in the two observation windows 1988-1990 and 1995-1997 is the following. Let us 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. We start by selecting employed and unemployed heads at the date of the first interview (e.g. March 1987).

For employed individuals 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

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[8]But notice that we do not know the order of this job spell: namely we do not know if it is following unemployment or a number of previous job-to-job transitions.

the calendar. The resulting duration is the tenure on the first job spell sampled. Each employed person in 1987 is then followed through his subsequent job changes (if any) with the respective durations 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. 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.

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. 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 $c_u(i) = 1$.

3.2 Wages information

The wage information in the calendar section follows a starting wage/ending wage structure particularly appropriate to evaluate wage changes upon job change. Within the calendar section period, any time an individual engages in a job-to-job transition 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 $w_1(i)$.

Even if this data structure is quite informative it generates the following problem. Focus on an individual transiting from job k to job $k + 1$. PSID will record two wages for job spell k: an ending wage for the transition from job k to job $k + 1$ and a starting wage for the transition from job $k - 1$ to job k. We have chosen to always keep the ending wage except in those cases in which the ending wage is missing. 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.[9]

Another issue concerning the wage variable is 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 is issue will be clarified and discussed in more details in section 4.1.

3.3   Descriptive Statistics

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. In addition, given the complexity to build the data set from the raw data 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[10] we have decided to use information on at most three consecutive job spells.

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 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.

Table 1 shows the descriptive statistics on the two samples 1988-1990 and 1995-1997. 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 602 individuals who started in employment in 1987. Their average tenure on the first job spell (t_1) is of about 46 months while the average hourly wage (w_1) is about 16 dollars an hour. 325

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[9]In our estimation sample the problem arises only for the second wage of those individuals experiencing at least three employment spells within the same cycle. The number of individuals in this situations 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.

[10]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.

of them had a second job spell (t_2) with a wage (w_2); t_2 is much shorter on average than t_1 because t_2 is often right censored. w_2 is larger than w_1 50% of the times: this quite large proportion of job-to-job transitions to a lower wage motivates our introduction of a reallocation shock. In terms of duration, out of the initial 602 spells, 31% are right censored ($c_1 = 1$); of the remaining 414, 21% end up in unemployment ($r_1 = 1$) and 325 in a job-to-job change with a second job spell. 65% of these are right censored ($c_2 = 1$), 22% of the remaining 115 end up in unemployment ($r_2 = 1$) while 90 find a third job with wage (w_3).

70 individuals started in unemployment in 1987 with an average tenure in unemployment (t_u) of a little more than 11 months, 16% are right censored ($c_u = 1$) and 59 found a job with tenure (t_1) and wage (w_u). 53% of these job spells are right censored ($c_1 = 1$); 39% of the remaining 28 end up in unemployment while 17 of them find a second job with wage w_2 and tenure t_2.

The descriptive statistics of 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 have an higher mean and higher 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 and variance. Employment durations are similar across the two periods and the proportion of job-to-job transitions followed by a wage loss is also comparable.

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.

4.1   Likelihood Function

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:

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

and the hazard rate out of employment is:

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

The unemployment duration contributions therefore are:

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

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.

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

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 many of them in the data and we are reluctant to assume measurement errors as their source. Following Jolivet, Postel-Vinay and Robin (2006), we prefer to explicitly 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 wage draw is between the previous wage and the reservation wage, we observe a job-to-job transition followed by a wage decrease. Lastly, we report the density of 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 kth 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.[11]

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.

$$
\begin{aligned}
f_w\left(w_u\right) &= \frac{g\left(w_u\right)}{\widetilde{G}\left(w^*\right)} \qquad\qquad\qquad\qquad\qquad (8) \\[2mm]
f_w\left(w_{k+1}, w_{k+1} > w_k | w_k\right) &= \frac{g\left(w_{k+1}\right)}{\widetilde{G}\left(w_k\right)} \times \frac{\left(\lambda_R + \lambda_E\right)\widetilde{G}\left(w_k\right)}{\lambda_E\widetilde{G}\left(w_k\right) + \lambda_R\widetilde{G}\left(w^*\right)} \\[2mm]
f_w\left(w_{k+1}, w_{k+1} < w_k | w_k\right) &= \frac{g\left(w_{k+1}\right)}{\widetilde{G}\left(w^*\right)} \times \frac{\lambda_R\left[G\left(w_k\right) - G\left(w^*\right)\right]}{\lambda_E\widetilde{G}\left(w_k\right) + \lambda_R\widetilde{G}\left(w^*\right)}
\end{aligned}
$$

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. The likelihood over wages and unemployment durations will then be the following where we denote vectors in bold,

---

[11]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.

the parameters to be estimated with the vector $\boldsymbol{\theta}$ and the last job with K:

$$
\begin{aligned}
L\left(t_u, \mathbf{w}, \mathbf{t}; \boldsymbol{\theta}\right) \quad = \quad & f_u\left(t_u\right) \qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad (9) \\
& \times f_e\left(t_1, w_2 > w_u | w_u\right) f_w\left(w_u\right) \\
& \times f_e\left(t_2, w_3 > w_2 | w_2\right) f_w\left(w_2, w_2 > w_u | w_u\right) \\
& \times \prod_{k=3}^{K-1} f_e\left(t_k, w_{k+1} > w_k | w_k\right) f_w\left(w_k, w_k > w_{k-1} | w_{k-1}\right) \\
& \times f_e\left(t_K, r_u = 1 | w_K\right) f_w\left(w_K, w_K > w_{K-1} | w_{K-1}\right)
\end{aligned}
$$

Notice that we have assumed that this individual will always experience wage increases at each new job. When this is not the case the likelihood should be changed accordingly as in the last row of the set of equations (8). Moreover, the individual is not experiencing any censored duration. Again, if this is the case the likelihood should be changed accordingly as described in the last row of the set of equations (7) and (6).

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 labor market career of the individuals from the last episode of unemployment. The likelihood for these types of individuals will then be:

$$
\begin{aligned}
L\left(\mathbf{w}, \mathbf{t}; \boldsymbol{\theta}\right) \quad = \quad & f_e\left(t_1, w_2 > w_1 | w_1\right) \qquad\qquad\qquad\qquad\qquad\qquad (10) \\
& \times \prod_{k=2}^{K-1} f_e\left(t_k, w_{k+1} > w_k | w_k\right) f_w\left(w_k, w_k > w_{k-1} | w_{k-1}\right) \\
& \times f_e\left(t_K, r_u = 1 | w_K\right) f_w\left(w_K, w_K > w_{K-1} | w_{K-1}\right)
\end{aligned}
$$

As before, this is a case with no censoring and where each job-to-job transitions lead to a job increase.

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 K increases. In our sample the maximum is $K = 4$. Even in this case 26 possible different likelihood are feasible. 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 limit $K = 3$. This means that we will exploit the information of each individual up to the second job-to-job transitions. We will then use the information on the third job-to-job transition just to decide if the transition has led to a job increase or a job decrease. For example, for the individual described in the likelihood (9) we will write the likelihood only on the data $\{t_u, w_u, w_2, t_1, t_2\}$ and we will use the information that $w_3 > w_2$. This procedure allows us to write the likelihood up to the third row of equation (9). Note that limiting our information in this way has no impact in terms of identification or asymptotic properties but only reduces efficiency. For a detailed version of the likelihood under this assumption and that includes the possibility of censoring, see Appendix 8.2.

4.2 Identification

The identification builds on Flinn and Heckman (1982) and on Flinn (2002). We will then just provide here a brief discussion of the main issues.

The primitives to be identified are:

$$\{\lambda_U, \lambda_E, \lambda_R, \eta, G(w), \rho, b\}$$

By using the non-parametric strongly consistent estimator proposed by Flinn and Heckman (1982):

$$\widehat{w^*} = \min_w \{\mathbf{w}\}$$

and by noticing that (ρ, b) enters the likelihood only through the reservation wage, we can reparametrize the model in terms of:

$$\{\lambda_U, \lambda_E, \lambda_R, \eta, G(w), w^*\}$$

As shown by Flinn and Heckman (1982), since we observe only accepted wages and not offered wages we need a parametric assumption on the sampling distribution if we want to identify all the primitives parameters and not simply the hazard rates. Following a standard assumption in the literature[12] we will assume that $G(w)$ is a lognormal probability distribution and we will denote its two parameters with (μ, σ) :

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

Under this assumption and since the non-parametric estimator $\widehat{w^*}$ is strongly consistent we can estimate the remaining parameters maximizing the concentrated likelihood that uses $\widehat{w^*}$ in place of the true value. In the concentrated likelihood the main sources of identification for each parameter are the following: the arrival rate of offers parameter λ_U is mainly identified by unemployment durations; the on-the-job arrival rate of offers parameter λ_E is mainly identified by employment durations followed by a wage increase and by right-censored employment durations; the reallocation shock parameter λ_R by employment durations followed by a wage decrease and by right-censored employment durations; the job termination parameter η by employment durations followed by unemployment and by right-censored employment durations; finally, the lognormal parameters (μ, σ) are mainly identified by the accepted wage distribution over w_u and over w_k when $k > 1$.

Given the identification of this reparametrized model, we can recover b by exploiting the reservation wage equilibrium equation (5) and by fixing a value for the discount rate ρ (in other words b is only jointly identified with ρ.) The details are reported in Appendix 8.1.

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[12] Contributions that assume a lognormal distribution in a similar context are, among others: Eckstein and Wolpin (1995); Dey and Flinn (2005) and Flabbi (2005). Other assumptions are feasibile 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.

5 Results

The results of the maximum likelihood estimation are reported in Table 2. The first two columns refer to the overall sample while the other four columns report results conditioning on education. Skilled workers are workers with some years of College completed or more (15 years of schooling completed or more) and unskilled workers with years of schooling completed less than that. Estimating the model separately on skilled and unskilled workers is important to investigate the potential different causes of the rise in instability across skill groups, an issue that was already signalled in Gottschalk and Moffitt (1994). Also the debate on the so called skill-biased technological change suggests that the labor market dynamic for skilled and unskilled workers could have been potentially very different over the period under consideration.

By looking first at the point estimates on the overall sample, we notice an increase over time in the arrival rate of offers on the job and in the variance of the wage offer distribution. The arrival rate of offers while unemployed, instead, decreases as, somewhat unexpectedly, the expected value of the wage offer distribution. The termination rate and the reallocation shock rate experience a smaller decrease. The estimates are overall reasonably precise with standard errors in the same range of other comparable studies.

It is difficult at this stage to draw a direct link from the estimated structural parameters and the observed earnings instability because each parameter generates non-linear impacts on the observed labor market dynamic. For this reason in the next section we will generate simulations to isolate the impact of some relevant parameters taking into account equilibrium effects. However, it is easy to identify two main candidates to explain a potential increase in earnings instability between 1988 and 1995: the increase in the on-the-job arrival rate and the increase in the variance of the sampling distribution.

Moving to the skill-specific results, the point estimates indicate that the increase in the variance $V(w)$ is concentrated among skilled workers while unskilled workers experience a decrease in the variance. On the other hand the increase in λ_E is common to both skill groups with a relative higher increase for the unskilled even if the arrival rate of offers on-the-job remains significantly higher for skilled workers over the entire period. Other notable differences across skill groups concern the reallocation shock (hitting at an increasing rate the unskilled and at a decreasing rate the skilled) and the arrival rate while unemployed (stable for the skilled and decreasing for the unskilled). These estimates confirm the importance of composition effects when looking at data aggregated over skills. For this reason the simulation and policy experiments in the next section will also be conducted by skill levels.

Again it is difficult to draw a direct inference from these structural parameters but results across skills seem consistent with mounting evidence suggesting that the growth in wage inequality is increasingly concentrated in the top end of the wage distribution.[13] Not only changes in actual wages, but also changes

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[13]Lemieux (2006b) finds that the return to post-secondary education increased sharply

in residual inequality also appear to be concentrated at the top end of the distribution.[14]

All this evidence points to potentially 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 the parameters $V(w)$ and λ_E, the skill biased technical change explanation is consistent with an increase in the variance of the wage offer distribution for the skilled but not for the unskilled workers.

Before moving to 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 informal evidence 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 an analysis that imposes very little structure on the data and we restrain from formal testing because of the low numerosity. Due to the low number of observations we are also conducting the analysis only at the aggregate level, pooling skilled and unskilled workers.

In Figure 1 we present the histogram of wages accepted immediately after an unemployment spell together with a smooth version of this empirical distribution (the kernel density estimation denoted by the dashed line) and with the density implied by the estimated model (denoted by the continuous line). Given the relatively low number of observations (59 on the 1988 sample and 60 on the 1995 sample) the empirical distribution is quite sensitive to the degree of smoothing as is evident from the different shape implied by the histogram and by the kernel density estimation. Based on the kernel density, model estimates for 1988 exhibits a very good fit while model estimates for 1996 imply a density with a lower mode at a lower location with respect to the kernel density. Again this mismatch on 1996 is quite sensitive to the degree of smoothing and it is clear how the kernel is "smoothing out" the mass of the first tow bins of the histogram while our model delivers a much sharper curvature in that area. Moreover, a few outliers, not presented in the figure, may play some role in the mismatch.[15]

---

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 that 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 disproportionally concentrated in the very top of the earnings distribution.

[14] For instance, Lemieux (2006a) shows that within-group inequality grew substantially among college-educated workers but changed little for most other groups. A related finding by Autor, Katz and Kearney (2008) is that "top end" residual inequality (e.g. the difference between the 90th and 50th percentile of the distribution of residuals, or the "90-50" gap) increased substantially while residual inequality at the low end (the 50-10 gap) actually declined.

[15] Not shown in the graph: for 1988 there is only one wage at about 73$/h while on 1996

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These qualifications aside, we conclude that overall the model is able to replicate the shape and location of accepted wages after a period of unemployment.

In Figure **??** 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. Moreover, like all nonparametric maximum likelihood estimators, it requires a large number of observations for precise estimation while in our sample we only have 70 unemployment durations for 1988 (out of which 11 are right censored) and 86 for 1995 (out of which 26 are right censored). We then conclude that the model implication of a constant hazard out of unemployment is not too restrictive on these data.

6   Policy Experiments

Given the estimated structural parameters it is possible to generate "counterfactual labor markets", i.e. labor market characterized by different combination of parameters estimated over the two periods. By appropriately combining different parameters we can evaluate the contribution of each of them on observed outcomes taking into account equilibrium effects. In other words: we cannot simply provide a decomposition on the observed data because each structural parameters has an impact on the equilibrium reservation wages and will generate different accepted wage distributions and durations distribution.

A reasonably straightforward way to implement these counterfactual experiments is by simulation: we can generate labor market careers by extracting wages and durations from the estimated distribution using pseudo-random number generators. 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 we record accepted wages, durations in each state and total time in the labor market. More details about the implementation of the simulation exercise are in Appendix 8.3.

We focus our attention on the two main determinants of the different earnings instability over the two periods: the higher arrival rate of offers on-the-job in 1995 and the higher variance of the wage offer distribution in 1995. The two "counterfactual labor markets" are built as follows: in the first experiment, labelled *Experiment* λ_E in Table 3, we fix all the parameters at the maximum likelihood point estimates for 1995 except the on-the-job arrival rate of offers which we fix at the maximum likelihood point estimate for 1988; in the second experiment, labelled *Experiment* $V(w)$ in Table 3, we fix all the parameters to 1995 except (μ, σ) which are fixed in such a way to generate the $E(w)$ estimated

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there are two outliers at about 94$/h and112$/h.

in 1995 but the $V(w)$ estimated in 1988. Clearly, many other experiments are possible but we reports results only on these two because they are the parameters more relevant in explaining the increase in earnings instability. An exception are the results for the unskilled workers where the substantial increase in λ_R is potentially more relevant and where the decrease in $V(w)$ is actually working in the opposite direction. For the unskilled we will discuss other experiments in the text without reporting the results in the Table.

We are then left to provide synthetic measures of earnings instability from these generated data. We compute four different sets of statistics that we report in Table 3. 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 dynamic. Finally, we compute the most popular measure of earnings instability in this literature: 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.

For comparison purposes, we also compute the same statistics on the two benchmark cases, that is on labor markets in which all the parameters are fixed at the estimated values for 1988 and for 1995. These benchmark economies are also useful to check if earnings instability has actually increased over the two periods. We can anticipate that by all our measures earnings instability has increased from the 1988 three-years period to the 1995 three-years period. The increase is mainly concentrated within the skilled workers group.

6.1 Cross-sectional inequality

We consider the following measures of inequality: coefficient of variation (CV), Theil entropy index (T) and Theil mean log deviation index ($T_{\log}$). The first is a common and straightforward measure of inequality while the other two have the advantage of being sensible to inequality in different parts of the distribution: T is more sensitive to the top part of the distribution while $T_{\log}$ is more sensitive to the bottom part. Defining with $\overline{x}$ the sample mean over a vector of x_i elements and with $SD(x)$ its standard deviation, the indexes are defined as follows:

$$
\begin{aligned}
CV &\equiv \frac{SD(x)}{\overline{x}} \\
T &\equiv \frac{1}{n}\sum_{i=1}^{n}\frac{x_i}{\overline{x}}\ln\left(\frac{x_i}{\overline{x}}\right) \\
T_{\log} &\equiv \frac{1}{n}\sum_{i=1}^{n}\ln\left(\frac{\overline{x}}{x_i}\right)
\end{aligned}
$$

We compute the previous measure of inequality on a cross-section of the data, that is for data in a given "year" where the year is defined by the time that has passed since the individuals entered the labor market. We need to

choose a year far enough from the beginning of time so as to approximate a steady state equilibrium. We choose the period between 120 and 132 months (i.e. labor market careers in the 11th year). Any 12-month period above 60 months give similar results.

The main results are the following: λ_E and $V(w)$ contribute approximately in the same way to the increase in overall cross-sectional inequality. Had λ_E and $V(w)$ stayed at their 1988 value, the coefficient of variation would have increased respectively to 0.773 and 0.783 instead of the actual 0.863. In other words, the impact of λ_E alone to the increase in cross-sectional inequality, once equilibrium effects are taken into account, is about 74% of the total increase in overall inequality from 1988 to 1995. The impact of $V(w)$ alone is about 66% of the total increase. The impact on overall inequality can be decomposed in impact on the wage inequality upon job change and upon finding a job right after unemployment. It is interesting to see the two components separately to learn which part of the labor market dynamics has been mainly affected. As expected, in the case of the mean preserving spread we observe a major increase in inequality exiting from unemployment even though it is still not enough to fully match the inequality in the benchmark case for 1995. The higher arrival rate of on-the-job offers in 1995 has instead a more pronounced impact on wage inequality upon job change.

A similar pattern is reproduced on the sample of skilled workers while in the case of unskilled workers both λ_E and $V(w)$ have contributed negatively to the growth of inequality: had they stayed at their 1988 value, inequality would have been higher in 1995. It is also worth mentioning that cross-sectional inequality has increased very little between the two periods for the unskilled workers. On this group, an experiment that explain some of this small increase in inequality is the combination of both the on-the-job wage offer shock and the reallocation shock fixed at their 1988 values. This experiment explains about 20% of the increase in the $T_{\log}$ index.

The main message we draw from these first set of statistics is that changes in the underlying sampling wage distribution are not enough to explain the increase in inequality: it is its interplay with search behavior and the transition between states dynamics that really generates what we see.

6.2   Lifetime inequality

Earnings instability is a dynamic concept and the previous cross-sectional inequality measures are only one aspect of it. Namely earnings instability is also influenced by how often and how long an individual is unemployed and changes jobs. A synthetic measures to describe this dynamic behavior is a measure of the overall welfare of an individual in her labor market career. We define this measure of lifetime welfare (LW) simply as the sum of the discounted values of the states that each individual occupies during her simulated labor market

career[16]:

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

$$where \quad : $$

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

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 $t_0 = 0$. Moreover, it will make the inequality measures very sensitive to a small number of outliers that take a lot of time to find their first job.

Comparing column three with column two in Table 3 we observe that had the arrival rate of offers on-the-job remained the same as in 1988 lifetime inequality would have actually be higher in the 1995 labor market (a coefficient of variation equal to 1.135 instead of 1.119). An higher arrival rate of offers on-the-job increases opportunities to move up the wage ladder and this higher mobility dominates the higher cross-sectional inequality to generate an overall lower lifetime inequality. Therefore the higher arrival rate of offers on-the-job does not explain any of the increase in lifetime inequality that we see between the two benchmark cases. The same result is obtained by skill levels even if with a smaller magnitude. For example, on skilled workers only the Theil indexes record a decrease in inequality as a result of an increase in λ_E.

The differential impact of λ_E 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 dynamic involved may lead to quite different conclusions. As in Flinn (2002) the lower cross-sectional inequality of Italy with respect to the U.S. was masking a higher lifetime inequality here the impact of a higher probability of receiving wage offers on-the-job increases cross-sectional inequality but also increase mobility opportunities leading to an actual decrease in lifetime inequality.

Results of the $V(w)$ experiments are instead more similar to the cross-sectional results: an increase in the wage offer variance increases lifetime inequality. On the overall sample the increase is significant (for example about 24% of the increase in the coefficient of variation). On skilled workers we obtain a similar result while on unskilled workers the opposite result since on this group the variance of the wage offer distribution decreases over time. Again, for unskilled workers the much higher probability of a reallocation shock and the much lower probability of receiving wage offers while unemployed play a major role.

To summarize, contrary to what seen for cross-sectional inequality, the increase in λ_E and $V(w)$ plays very different role: $V(w)$ is the main source of

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[16] This is similar to the measure used in Flinn 2002, see in particular his Appendix B.

the increase in lifetime inequality between the two periods while λ_E is actually responsible for a reduction of lifetime inequality over time.

6.3 Labor Market Dynamics Measures

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.[17]

We provide similar measures on our generated data: the median duration of employment and unemployment spells. Since individual labor market experience differs, the duration of employment and unemployment spells are reported as proportions of the total labor market experience of each individual. We also report the proportion of total labor market experience spent in unemployment and the median number of jobs in the entire labor market career. Last, we add the median wage growth between jobs and the variance of wage growth between jobs (the model has no growth within job).

The main results, reported in the third panel of Table 3 are the following.

First, looking at the statistics for the two benchmark cases, the overall picture is of increasing instability. The median duration of an employment spell has gone down between 1988 and 1996 and so has the median duration of an unemployment spell. Another indicator of the increase in turbulence is the rise of the variance of between-job wage growth. The number of jobs in a lifetime, the proportion of time spent in unemployment and the median wage growth between jobs have instead remained stable (or slightly declining).

Second, the counterfactual exercises keeping λ_E at the 1988 level or $V(w)$ at the 1988 level do not seem to give clear indications. In the overall sample the increase in λ_E gives a positive but small contribution to the decrease in the median employment tenure and a big contribution to the decrease of the median unemployment tenure. The increase in $V(w)$ gives no contribution to either of them. The effects of both λ_E and $V(w)$ are similar across skill groups.

Finally, the increased instability is reflected mainly on the employment dynamics measures for the unskilled workers (decline of the median employment duration) and on the wage dynamics measures for the skilled workers (increase in the variance of $\Delta \log w$ between jobs).

6.4 Gottschalk and Moffitt decomposition

In this section 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 consider wages w_{it} composed of an individual fixed effect μ_i and a transitory shock v_{it}. The two components are orthogonal to each

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[17]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.

other and are allowed to vary over time with the respective loading factors ϕ_t and π_t:

$$\log w_{it} = \phi_t \mu_i + \pi_t v_{it} \tag{11}$$

where $logw_{it}$ is the log of the simulated wage and 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 (11) using a minimum distance estimator. The results of this exercise are shown at the bottom of Table 3 where we show the average of the total, transitory and permanent variance and in Figure 3 and 4 where we 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 the transitory variance of wages between 1988 and 1996 by using the benchmark labor markets. The increase in the transitory variance (about 16%) is larger than the increase in the permanent variance. The calculation of the transitory variance on the sample generated keeping λ_E fixed at the 1988 level shows that this experiment accounts for around 38% of the increase in the transitory variance between the two periods: i.e. the increase in λ_E from 1988 to 1996 accounts for the remaining 62%. Keeping $V(w)$ fixed at the 1988 level accounts for about 71% of the increase in the transitory variance between the two periods: i.e. the increase in $V(w)$ from 1988 to 1996 accounts for the remaining 29%.

We conclude that a larger part of the increase in the transitory variance between 1988 and 1996 is correlated with the change in λ_E during this period rather than with the change of the variance of the underlying wage offer distribution. This goes in favor of our interpretation that changes in individual mobility are fundamental in explaining the evolution of wage dispersion although their effect is confounded by other intervening factors.

Also consistent with the literature is the finding that the increase in the total and transitory variance of wages among the skilled (some college or more) is larger than among the unskilled. Figure 4 shows that the transitory variance of wages among the skilled grew substantially over the two periods while it did not grow among the unskilled. The same Figure shows that both λ_E and $V(w)$ significantly contributed to the growth of instability among skilled workers while they do not explain much of the evolution of the transitory variance of wages among unskilled workers.

7   Conclusion

Many contributions suggest that earnings instability has 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 inequality and labor market dynamic in explaining earnings instability. To study the evolution over time of these different components we extract two estimation samples (late 1980s and late1990s) from the Calendar Section of the PSID. Also based on

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descriptive statistics from these data we add a non-standard feature to our on-the-job search model: we introduce a reallocation shock able to generate the significant proportion of job-to-job transitions followed by a wage decrease.

We find that the two main structural parameters able to explain a potential increase in earnings instability between 1988 and 1995 are the on-the-job arrival rate and the variance of the wage offer distribution: they both increase in the late 1990s. The arrival rate of offers while unemployed is estimated to be lower in the late 1990s while the reallocation shocks and the job termination shocks play a minor role in explaining differentials between the two periods. We also estimate substantial differences by skill levels: only skilled workers experience an increase in the variance of the wage offer distribution while unskilled workers experience a substantial increase in the probability of a reallocation shock.

Based on the point estimates of the structural model we generate conterfactual experiments by simulations, that is we generate simulated labor market histories from labor market with appropriate combinations of parameters. The objective is to isolate the contribution of some parameters of interest to the increase in earnings instability taking into account equilibrium effects. We use four metrics to evaluate earnings instability: cross-sectional inequality; lifetime inequality; durations and transitions statistics; and the Gottschalk and Moffitt (1994) volatility decomposition. The experiments indicate that both the increase in λ_E and $V(w)$ have contributed to the increase in cross sectional inequality (they explain between 66% and 74% of the increase) but that only the increase in $V(w)$ explains some of the increase in lifetime inequality (about 24% of it). Separate results on skilled and unskilled individuals indicate that a similar pattern is reproduced on the sample of skilled workers but not on the sample of unskilled workers. For the unskilled both λ_E and $V(w)$ have contributed negatively to the growth of inequality that, however, has increased much less on this group. Using the Gottschalk and Moffitt decomposition we find that a larger part of the increase in the transitory variance between 1988 and 1996 is correlated with the change in λ_E than with the change in $V(w)$.

These results are complementary to the literature on wage inequality: we think using structural estimates contributes to shed light on the role of job mobility which is often confounded with other factors in simple descriptive evidence. One of the main contribution of this paper is then giving a quantitative assessment of the importance of on-the-job search in explaining changes in earnings instability. The conclusion is that the estimated larger activity in on-the-job search between the late 1980s and late 1990s has increased cross-sectional inequality but not lifetime inequality. However, this impact varies by skill levels.

8   Appendix

8.1   Recovering (b, ρ)

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

$$U = W\left(w^*\right)$$

we get:

$$U = \frac{w^* + \left[\eta + \lambda_R G\left(w^*\right)\right] U + \lambda_E \int_{w^*} W\left(w'\right) dG\left(w'\right) + \lambda_R \int_{w^*} W\left(w'\right) dG\left(w'\right)}{\rho + \lambda_E \widetilde{G}\left(w^*\right) + \lambda_R + \eta}$$

$$U = \frac{w^* + \left(\lambda_E + \lambda_R\right) \int_{w^*} W\left(w'\right) dG\left(w'\right)}{\rho + \left(\lambda_E + \lambda_R\right) \widetilde{G}\left(w^*\right)} \tag{12}$$

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:

$$\left(\rho + \lambda_E \widetilde{G}\left(w\right) + \lambda_R + \eta\right) W\left(w\right) = w + \left[\eta + \lambda_R G\left(w^*\right)\right] \frac{w^* + \left(\lambda_E + \lambda_R\right) \int_{w^*} W\left(w'\right) dG\left(w'\right)}{\rho + \left(\lambda_E + \lambda_R\right) \widetilde{G}\left(w^*\right)}$$

$$+ \lambda_E \int_w W\left(w'\right) dG\left(w'\right)$$

$$+ \lambda_R \int_{w^*} W\left(w'\right) dG\left(w'\right)$$

which is an integral equation independent from b that we can solve for $W\left(w\right)$. 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 $W\left(w\right)$, recover b as:

$$b = \frac{\rho + \lambda_U \widetilde{G}\left(w^*\right)}{\rho + \left(\lambda_E + \lambda_R\right) \widetilde{G}\left(w^*\right)} \left[w^* + \left(\lambda_E + \lambda_R\right) \int_{w^*} W\left(w'\right) dG\left(w'\right)\right] - \lambda_U \int_{w^*} W\left(w'\right) dG\left(w'\right) \tag{13}$$

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.

8.2 An extended version of the likelihood function

We report here an extended version of the likelihood function that include censoring and the possibility of wage increase and decrease following a job-to-job transition. This is the formulation we actually use in estimation. Since we may not observe all the variables on all the individuals we need to add the following indicators, again defined at the individual level but omitting the index i:

$$\chi\left(x\right) = 1 \text{ if we observe } x$$
$$\text{where } x \in \{w_u, w_1, w_2, t_u\}$$

We are now ready to present the individual loglikelihood of one cycle for individuals starting in the unemployment state:

$$
\begin{aligned}
&\ln L_i \\
=\ & \chi\left(t_u\right) c_u \ln f_u\left(t_u, c_u=1\right) \\
&+\chi\left(t_u\right)\left(1-c_u\right) c_1\left[\ln f_u\left(t_u\right) f_e\left(t_1, c_1=1 \mid w_u\right) f_w\left(w_u\right)\right] \\
&+\chi\left(t_u\right)\left(1-c_u\right)\left(1-c_1\right) r_1\left[\ln f_u\left(t_u\right) f_e\left(t_1, r_1=1 \mid w_u\right) f_w\left(w_u\right)\right] \\
&+\chi\left(t_u\right)\left(1-c_u\right)\left(1-c_1\right)\left(1-r_1\right) \mathbf{I}_{\left\{w_2>w_u\right\}} c_2 \\
&\times\left[\begin{array}{l}
\ln f_u\left(t_u\right) f_e\left(t_1, w_2>w_u \mid w_u\right) f_w\left(w_u\right) \\
\times f_e\left(t_2, c_2=1 \mid w_2\right) f_w\left(w_2, w_2>w_u \mid w_u\right)
\end{array}\right] \\
&+\chi\left(t_u\right)\left(1-c_u\right)\left(1-c_1\right)\left(1-r_1\right) \mathbf{I}_{\left\{w_2>w_u\right\}}\left(1-c_2\right) r_2 \\
&\times\left[\begin{array}{l}
\ln f_u\left(t_u\right) f_e\left(t_1, w_2>w_u \mid w_u\right) f_w\left(w_u\right) \\
\times f_e\left(t_2, r_2=1 \mid w_2\right) f_w\left(w_2, w_2>w_u \mid w_u\right)
\end{array}\right] \\
&+\chi\left(t_u\right)\left(1-c_u\right)\left(1-c_1\right)\left(1-r_1\right) \mathbf{I}_{\left\{w_2>w_u\right\}}\left(1-c_2\right)\left(1-r_2\right) \mathbf{I}_{\left\{w_3>w_2\right\}} \\
&\times\left[\begin{array}{l}
\ln f_u\left(t_u\right) f_e\left(t_1, w_2>w_u \mid w_u\right) f_w\left(w_u\right) \\
\times f_e\left(t_2, w_3>w_2 \mid w_2\right) f_w\left(w_2, w_2>w_u \mid w_u\right)
\end{array}\right] \\
&+\chi\left(t_u\right)\left(1-c_u\right)\left(1-c_1\right)\left(1-r_1\right) \mathbf{I}_{\left\{w_2>w_u\right\}}\left(1-c_2\right)\left(1-r_2\right)\left(1-\mathbf{I}_{\left\{w_3>w_2\right\}}\right) \\
&\times\left[\begin{array}{l}
\ln f_u\left(t_u\right) f_e\left(t_1, w_2>w_u \mid w_u\right) f_w\left(w_u\right) \\
\times f_e\left(t_2, w_3<w_2 \mid w_2\right) f_w\left(w_2, w_2>w_u \mid w_u\right)
\end{array}\right] \\
&+\chi\left(t_u\right)\left(1-c_u\right)\left(1-c_1\right)\left(1-r_1\right)\left(1-\mathbf{I}_{\left\{w_2>w_u\right\}}\right) c_2 \\
&\times\left[\begin{array}{l}
\ln f_u\left(t_u\right) f_e\left(t_1, w_2<w_u \mid w_u\right) f_w\left(w_u\right) \\
\times f_e\left(t_2, c_2=1 \mid w_2\right) f_w\left(w_2, w_2<w_u \mid w_u\right)
\end{array}\right] \\
&+\chi\left(t_u\right)\left(1-c_u\right)\left(1-c_1\right)\left(1-r_1\right)\left(1-\mathbf{I}_{\left\{w_2>w_u\right\}}\right)\left(1-c_2\right) r_2 \\
&\times\left[\begin{array}{l}
\ln f_u\left(t_u\right) f_e\left(t_1, w_2<w_u \mid w_u\right) f_w\left(w_u\right) \\
\times f_e\left(t_2, r_2=1 \mid w_2\right) f_w\left(w_2, w_2<w_u \mid w_u\right)
\end{array}\right] \\
&+\chi\left(t_u\right)\left(1-c_u\right)\left(1-c_1\right)\left(1-r_1\right)\left(1-\mathbf{I}_{\left\{w_2>w_u\right\}}\right)\left(1-c_2\right)\left(1-r_2\right) \mathbf{I}_{\left\{w_3>w_2\right\}} \\
&\times\left[\begin{array}{l}
\ln f_u\left(t_u\right) f_e\left(t_1, w_2<w_u \mid w_u\right) f_w\left(w_u\right) \\
\times f_e\left(t_2, w_3>w_2 \mid w_2\right) f_w\left(w_2, w_2<w_u \mid w_u\right)
\end{array}\right] \\
&+\chi\left(t_u\right)\left(1-c_u\right)\left(1-c_1\right)\left(1-r_1\right)\left(1-\mathbf{I}_{\left\{w_2>w_u\right\}}\right)\left(1-c_2\right)\left(1-r_2\right)\left(1-\mathbf{I}_{\left\{w_3>w_2\right\}}\right) \\
&\times\left[\begin{array}{l}
\ln f_u\left(t_u\right) f_e\left(t_1, w_2<w_u \mid w_u\right) f_w\left(w_u\right) \\
\times f_e\left(t_2, w_3<w_2 \mid w_2\right) f_w\left(w_2, w_2<w_u \mid w_u\right)
\end{array}\right]
\end{aligned}
$$

For individuals starting in the employment state, with wage at that job denoted by w_1, the loglikelihood is very similar. We will then report just the

first few lines that are enough to underline the differences:

$$\ln L_i$$
$$= (1 - \chi(t_u)) c_1 [\ln f_e(t_1, c_1 = 1|w_1)]$$
$$+ (1 - \chi(t_u))(1 - c_1) r_1 [\ln f_e(t_1, r_1 = 1|w_1)]$$
$$+ (1 - \chi(t_u))(1 - c_1)(1 - r_1) \mathbf{I}_{\{w_2 > w_1\}} c_2$$
$$\times \begin{bmatrix} \ln f_e(t_1, w_2 > w_1|w_1) \\ \times f_e(t_2, c_2 = 1|w_2) f_w(w_2, w_2 > w_1|w_1) \end{bmatrix}$$
$$.$$
$$.$$
$$.$$

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

	1988			1995		
	N	Mean	S.D.	N	Mean	S.D.
Starting in Unemployment:	70			86		
w_u	59	11.60	10.53	60	13.29	18.15
w_2	17	13.68	10.07	25	8.59	2.58
w_3	1	6.59		1	7.30	.
t_u	70	11.46	11.70	86	14.79	14.44
t_1	59	13.95	9.86	60	12.70	9.41
t_2	17	10.12	7.13	25	10.44	7.34
c_u	70	0.16		86	0.30	
$c_1\|c_u=0$	59	0.53		60	0.43	
$r_1\|c_u=0,c_1=0$	28	0.39		34	0.26	
$c_2\|c_u=0,c_1=0,r_1=0$	17	0.71		25	0.84	
$r_2\|c_u=0,c_1=0,r_1=0,c_2=0$	5	0.80		4	0.75	
$w_2>w_u\|c_u=0,c_1=0,r_1=0$	17	0.71		25	0.56	
$w_3>w_2\|c_u=0,c_1=0,r_1=0,c_2=0,r_2=0$	1	1.00		1	1.00	.
Starting in Employment:	602			467		
w_1	602	16.02	11.78	467	15.51	14.95
w_2	325	16.67	10.41	352	16.33	17.09
w_3	90	17.89	12.78	35	12.38	5.30
t_1	602	46.41	60.27	467	52.13	70.57
t_2	325	14.32	9.79	352	14.95	10.05
c_1	602	0.31		467	0.13	
$r_1\|c_1=0$	414	0.21		405	0.13	
$c_2\|c_1=0,r_1=0$	325	0.65		352	0.81	
$r_2\|c_1=0,r_1=0,c_2=0$	115	0.22		67	0.48	
$w_2>w_1$	325	0.50		352	0.58	
$w_3>w_2\|c_1=0,r_1=0,c_2=0,r_2=0$	90	0.59		35	0.54	

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.

Table 2: Maximum Likelihood Estimates

	All		Skilled		Unskilled	
	1988	1995	1988	1995	1988	1995
λ_U	0.0739	0.0508	0.1049	0.1038	0.0704	0.0483
	(0.0096)	(0.0066)	(0.0351)	(0.0400)	(0.0100)	(0.0068)
λ_E	0.0123	0.0192	0.0243	0.0252	0.0103	0.0145
	(0.0018)	(0.0025)	(0.0053)	(0.0062)	(0.0020)	(0.0025)
λ_R	0.0090	0.0088	0.0091	0.0063	0.0087	0.0103
	(0.0006)	(0.0006)	(0.0013)	(0.0012)	(0.0007)	(0.0008)
η	0.0038	0.0026	0.0013	0.0020	0.0046	0.0032
	(0.0003)	(0.0004)	(0.0005)	(0.0008)	(0.0004)	(0.0004)
μ	2.3181	2.0244	2.7475	2.4562	2.1988	2.0640
	(0.0379)	(0.0625)	(0.0642)	(0.1205)	(0.0369)	(0.0427)
σ	0.6698	0.8055	0.4574	0.5708	0.5699	0.5979
	(0.0241)	(0.0363)	(0.0391)	(0.0661)	(0.0234)	(0.0271)
$E\left(w\right)$	12.7105	10.4726	17.3245	13.7231	10.6039	9.4188
	(0.4405)	(0.4912)	(0.9464)	(1.2818)	(0.3663)	(0.3486)
$V\left(w\right)$	91.4723	100.1659	69.8465	72.5370	43.1504	38.1200
	(10.4608)	(12.9418)	(12.2031)	(15.5010)	(5.1371)	(4.5972)
w^*	1.7639	2.3381	7.2361	6.0373	1.7639	2.3381
N	665	545	146	106	493	382
$Loglik$	-5070.36	-4886.33	-1141.92	-862.70	-3578.95	-3379.22

Notes: Asymptotic standard errors in parentheses. Skilled defines individuals who have completed more than 15 years of education; Unskilled individuals who have completed 15 or less years of education.

Table 3: Policy Experiments

	All				Skilled				Unskilled			
	Benchmark		Experiment		Benchmark		Experiment		Benchmark		Experiment	
	1988	1995	λ_E	$V(w)$	1988	1995	λ_E	$V(w)$	1988	1995	λ_E	$V(w)$
Cross-sectional inequality measure: wages												
All												
CV	0.741	0.863	0.773	0.783	0.436	0.553	0.540	0.515	0.563	0.583	0.597	0.653
T	0.208	0.261	0.231	0.240	0.086	0.124	0.122	0.114	0.141	0.147	0.151	0.174
$T_{\log}$	0.204	0.246	0.223	0.234	0.084	0.117	0.116	0.110	0.143	0.148	0.148	0.171
Out of U												
CV	0.650	0.968	0.705	0.891	0.445	0.715	0.564	0.539	0.603	0.550	0.620	0.667
T	0.185	0.299	0.207	0.277	0.091	0.168	0.130	0.122	0.154	0.137	0.162	0.183
$T_{\log}$	0.194	0.271	0.203	0.250	0.090	0.144	0.120	0.114	0.152	0.139	0.156	0.177
Out of E												
CV	0.754	0.831	0.783	0.753	0.434	0.491	0.525	0.499	0.538	0.585	0.588	0.645
T	0.210	0.247	0.235	0.227	0.085	0.107	0.116	0.108	0.131	0.147	0.146	0.170
$T_{\log}$	0.203	0.234	0.226	0.224	0.083	0.105	0.111	0.104	0.134	0.148	0.144	0.167
Lifetime inequality measure: welfare												
CV	0.936	1.119	1.135	1.075	0.547	0.655	0.653	0.642	0.795	0.898	0.904	0.934
T	0.350	0.440	0.453	0.420	0.141	0.187	0.189	0.182	0.274	0.345	0.348	0.361
$T_{\log}$	0.384	0.545	0.570	0.525	0.161	0.207	0.210	0.202	0.317	0.469	0.473	0.484
Labor market dynamic measures:												
$m[t_e]$	0.202	0.185	0.193	0.184	0.192	0.208	0.211	0.207	0.205	0.182	0.188	0.183
$m[t_u]$	0.131	0.066	0.130	0.066	0.137	0.034	0.125	0.034	0.126	0.066	0.131	0.067
Av. # jobs	7.9	8.1	7.79	8.2	8.8	7.9	7.9	8	7.72	8.25	8.09	8.2
$m[\sum t_u]$	0.041	0.058	0.061	0.056	0.022	0.030	0.030	0.029	0.046	0.056	0.057	0.058
$\Delta\log(w)$	0.206	0.185	0.226	0.026	0.127	0.218	0.194	0.014	0.186	0.113	0.16	0.016
$V[\Delta\log(w)]$	0.930	0.948	0.968	0.952	0.595	0.621	0.666	0.655	0.8	0.78	0.79	0.791
Gottschalk-Moffitt earnings volatility decomposition:												
Total	0.465	0.546	0.499	0.522	0.186	0.249	0.247	0.242	0.344	0.346	0.332	0.373
Transitory	0.418	0.493	0.447	0.471	0.170	0.225	0.221	0.219	0.308	0.312	0.299	0.336
Permanent	0.047	0.053	0.052	0.050	0.015	0.023	0.025	0.023	0.036	0.033	0.033	0.036

Notes: The reported measures of inequality are: coefficient of variation (CV), Theil entropy index (T) and Theil mean log deviation index $(T_{\log})$. $m[\,]$ denotes the median; $V[\,]$ denotes the variance. All the durations are computed relative to the individual labor market career.
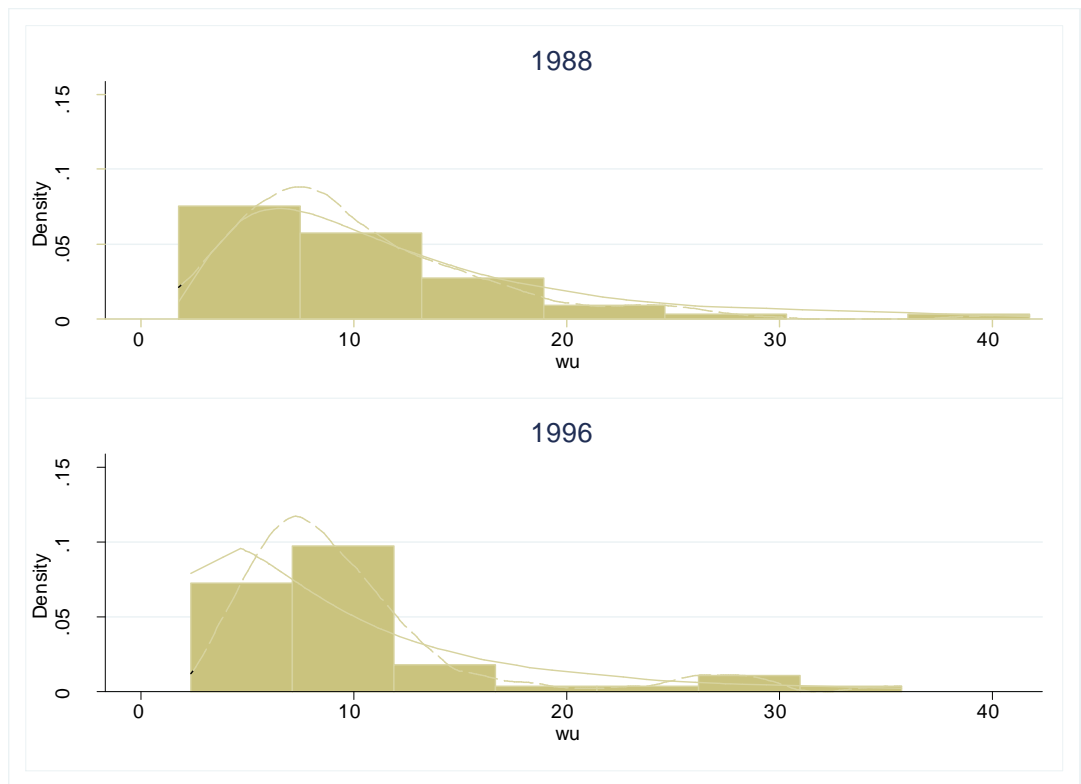
Figure 1: **Fit of the model on first wage after unemployment** (w_u).

Note: Continuous line is the predicted density of the estimated model; dashed line is a kernel density.
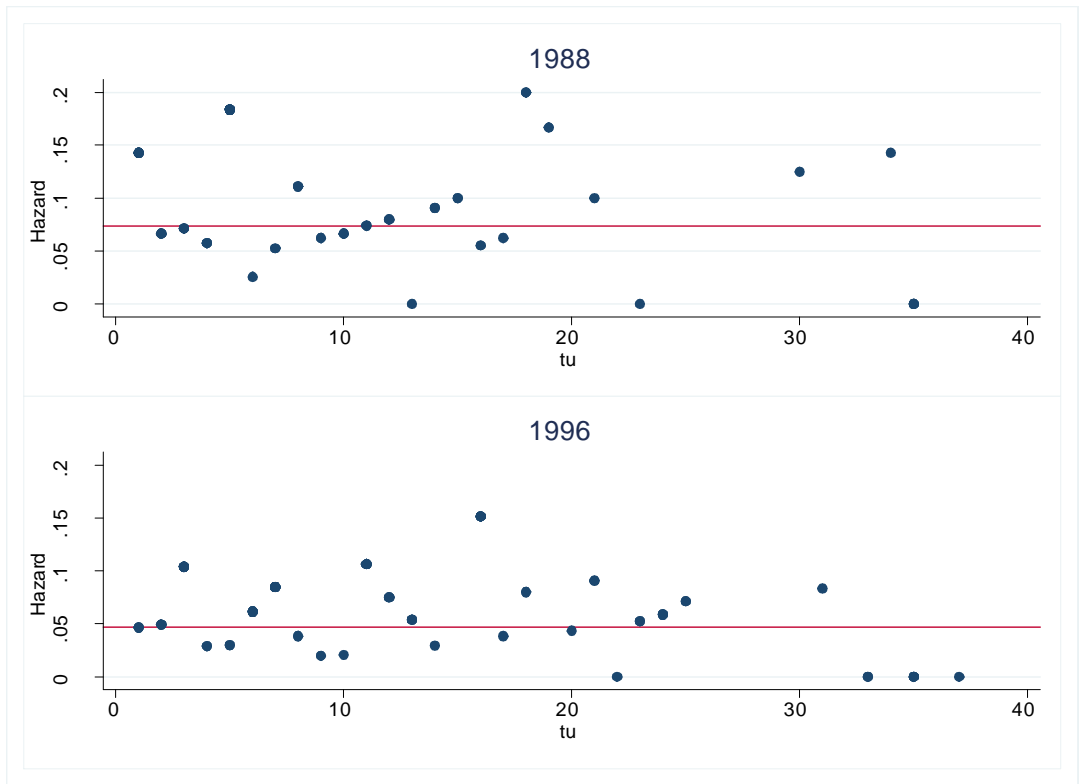
Figure 2: **Fit of the model on unemployment durations** (t_u)**.**

Note: Horizontal line is the hazard rate out of unemployment implied by the estimated model; dots are the empirical hazard out of unemployment.
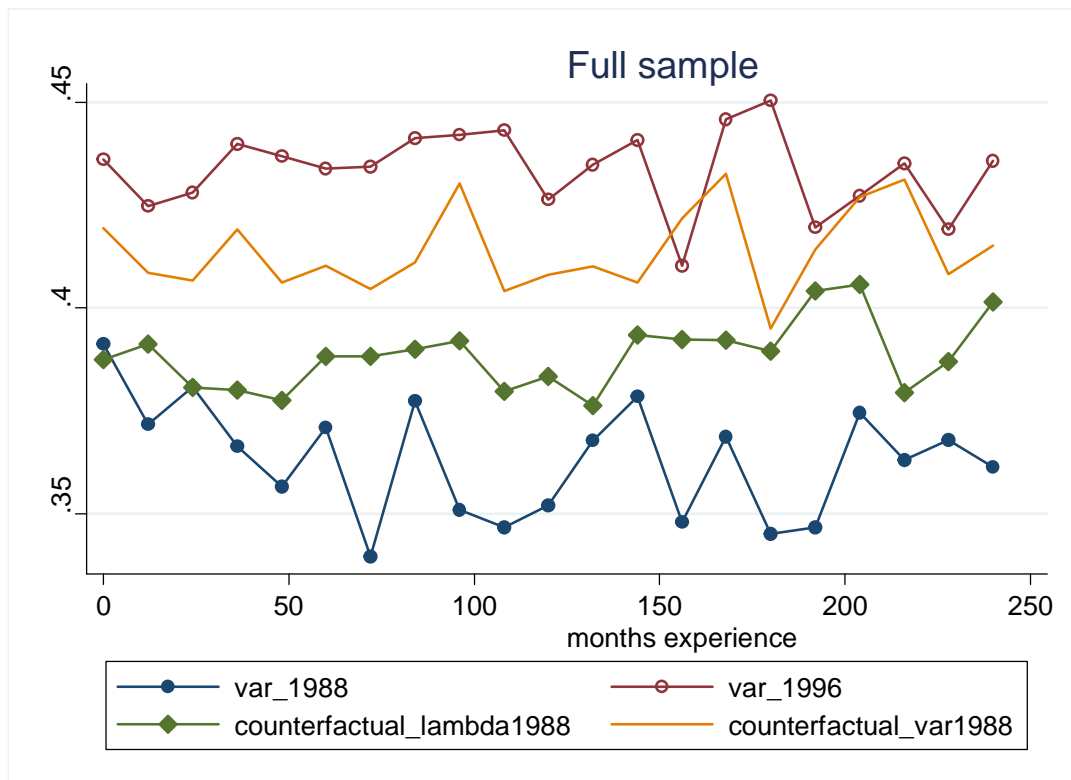
Figure 3: Transitory variance of wages calculated on the 1988 and 1996 samples and on the counterfactual samples generated keeping λ_E and $V(w)$ fixed at their 1988 level.
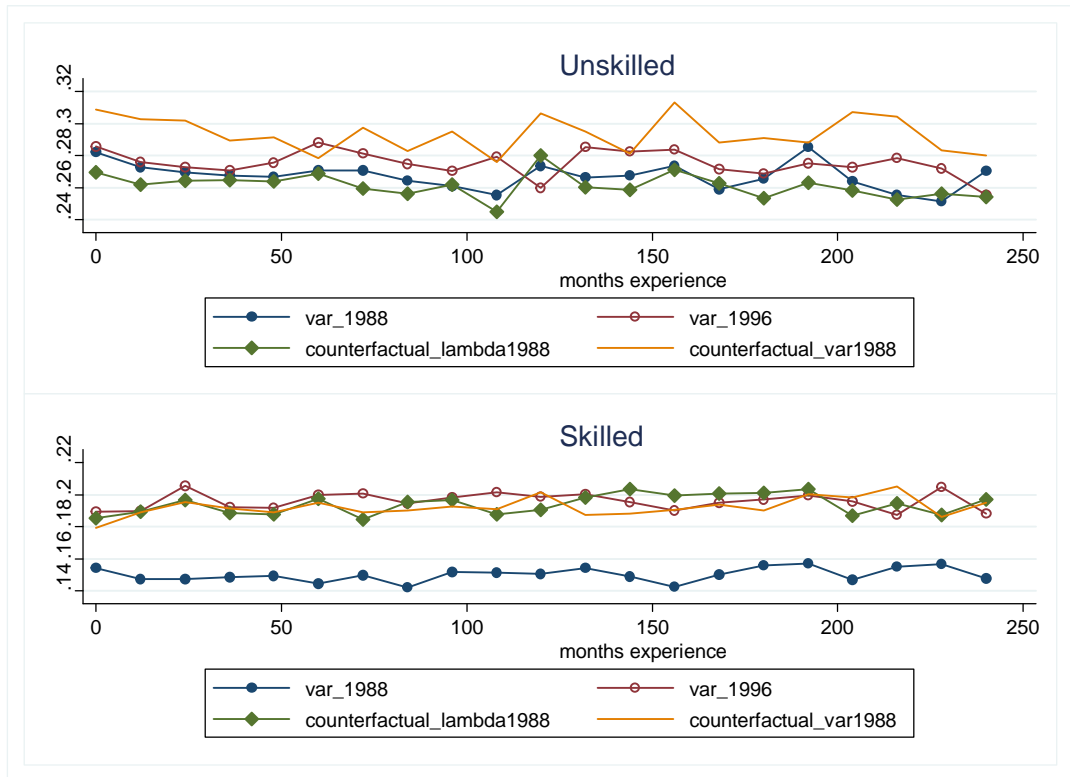
Figure 4: Transitory variance of wages of skilled and unskilled workers calculated on the 1988 and 1996 samples and on the counterfactual samples generated keeping λ_E and $V(w)$ fixed at their 1988 level.