

Inequality in Unemployment Risk and in Wages

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Abstract

Distinguishing between the relative roles of skills and luck in the determination of wages is a main concern for economic policy. Variation in observed characteristics of workers and firms typically account for one third of total variance in wages in the US. Luck, as a result of frictions in the process of job search, might explain some of the remaining proportion, but search models can only fill a tiny part of this gap when calibrated to mean transition rates. The aim of this paper is to highlight the existence of heterogeneity in finding and separation rates and to show its impact on inequality. In particular, we first reassess the role of frictions in wage dispersion by introducing heterogeneity in unemployment risk, both as exogenous fixed heterogeneity and with some duration dependence. Secondly, to endogenize this heterogeneity, we borrow from Ljungqvist and Sargent (1998), extending it to account for endogenous separation, and build a quantitative search model with human capital accumulation. In this context, a job is valuable for the inexperienced worker not only because of the wage but also for the opportunity to accumulate skills. At the same time, the unemployment spell is damaging for an experienced worker not only because of the foregone earnings but also for the loss of human capital that it entails. Thus, reservation wages and transition rates depend on individual labor market histories. We calibrate the model to match the observed heterogeneity in finding and separation rates and show that the implied wage dispersion is almost the residual wage dispersion in the data. Furthermore, when we shock the model to account for the change in human capital accumulation process in the US economy, we are able to explain all of the increase in inequality over the last decades. We conclude that heterogeneity in unemployment risk and the incentives related to human capital accumulation and depreciation are main drivers of frictional wage dispersions.

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1 Introduction

Wages differ for observationally equivalent workers. Even after considering all the sources of distinctions between jobs, meaning variables related to human capital, discrimination and compensating differentials, the spread between wages persists. The remaining component could be partially explained by measurement error, unobserved heterogeneity and... luck.

In fact, luck is a main issue in labor markets with frictions: in a context in which workers can get a job only after searching for vacancies with heterogeneous characteristics, the speed and order in which these vacancies are found determine the outcome of the search, that is, the wage level.

Frictional wage dispersion, the wage inequality inherently associated to luck in a context of search frictions, is an elusive concept: it has no clear measurable counterpart. On the one hand, empirical approaches have commonly estimated the residual wage dispersion after controlling for observables. In general, these regressions account for only one third of total variance of log wages in the US; the remaining is potentially due to frictions. On the other hand, more structural measures using canonical search models (such as McCall (1970)), calibrated to represent US economy, can only generate a tiny part of this residual dispersion (only 1/20, as proved by Hornstein et al. (2007)). Is the difference only due to unobserved heterogeneity or to measurement error? Or are the simple specifications of search models understating the degree of frictional wage dispersion?

This paper emphasizes the fact that search frictions affect workers differently. Transition rates into and out of unemployment are very heterogeneous between workers. Evidence of this is that both rates exhibit significant duration dependence after controlling for observables. While this shape can be driven by "true" duration dependence or by unobservables fixed characteristics, the heterogeneity is apparent.

The aim of this paper is to show that once this heterogeneity in the incidence of frictions is included, frictional wage dispersion increases dramatically. We show this by a simple exercise and with a quantitative model.

We first analyze a simple Mc Call model. Instead of using mean transition rates, we consider the existence of different types of workers, characterized by their unemployment risk (finding and separation rates), and calibrate the model accordingly. We consider two different setups: one in which differences between workers are permanent; an alternative one with transitions between types. In this second case, a worker can transit to the higher unemployment risk type during unemployment spell and can improve to the lower unemployment risk type with employment. With this simple extension, frictional wage dispersion increases dramatically. The economic mechanism of this result is that workers with higher unemployment risk are willing to accept lower wages to avoid extending unemployment; in other words, their possibilities to find and keep a job is relatively low, what makes them less choosy. When considering transition between types dispersion is further increased because of additional incentives: continuing in unemployment can drive the worker to the worst type, what reduces reservation

wages of the better type.

We then consider a simple quantitative model in which heterogeneity in transition rates arise endogenously. We borrow from Ljungqvist and Sargent (1998) (LS from now on) search model with human capital accumulation, and we extend it by considering shocks on the job to introduce endogenous separations. In this model, skills depreciate during the unemployment spell and accumulate on the job. Furthermore, in the case of separation, some random proportion of skills are lost at the moment of displacement. These differences in skills imply also differences in the finding and separation rates: low skilled workers face both lower finding rate and higher separation rate; hence, are the ones with higher unemployment risk. This is the result of a lower incentive to work for this kind of workers, given that they would receive lower labor earnings than high skilled workers and, thus, are not quite attached to employment.

The role of human capital accumulation process is crucial for addressing the inequality in unemployment risk and in wages. In this context, a job is valuable because it is the way to accumulate skills. For this reason, unemployed workers (particularly unskilled ones) will accept lower wages in order to improve their prospects through human capital accumulation. On the other hand, skilled workers would try to reduce the length of unemployment spell, because of the progressive depreciation of human capital that it implies, reducing the reservation wage. Finally, being laid off is particularly problematic for skilled employed workers, because some proportion of human capital will be lost at displacement. Thus, employed workers would accept a wage cut in order to avoid layoff. On the whole, reservation wages (while unemployed and while employed) will be reduced, increasing wage dispersion.

Our quantitative exercises show that this model is able to explain almost all the residual wage dispersion.¹ Additionally, it generates most of the observed heterogeneity in finding and separation rates.

As a robustness check of the model, we analyze its ability to reproduce the rise in wage dispersion observed in the US between 70s and 90s. Many authors have stressed the significance of this increase in inequality (Nagypal and Eckstein (2004), Bowlus and Robin (2004), Katz and Autor (1999), Juhn et al. (1993)), motivating a number of papers that attempted to explain it in a competitive labor market framework (Gould (2002), Lee and Wolpin (2006), and Topel (1997)) or in a search context (Acemoglu (1999), Kambourov and Manovskii (2004), and Violante (2002) among others). But the role of search behavior of unemployed workers has not been stressed in the explanations. We raise this issue motivated in the fact that search behavior has not remained constant during this period. Particularly, we show that the variance of unemployment duration has grown hand-in-hand with wage dispersion.

¹It is important to stress that the wage dispersion that we report is not related to dispersion in skills, but only on labor income after controlling for skills (i.e. the dispersion of w and not of wh , where h is the level of human capital). This provides a more accurate measure of frictional dispersion and disentangles the relative effects of skills and luck. This is an important difference with other papers, in which controls of the impact of skills or observables are not included (Kambourov and Manovskii (2004), Violante (2002) and Papp (2009)).

We argue that human capital accumulation and depreciation process has also changed through this period and is the economic force behind the increase in inequality both of unemployment risk and of wages. The main shock is the increase in returns to human capital (in particular to experience and tenure), more frequent job-specific idiosyncratic shocks and changes in wage loss at displacement. When we include these issues in the model accordingly, we find that it generates an important increase in wage dispersion.

Our paper relates to a very diverse literature. Firstly, Hornstein et al. (2007) (HKV from now on) have shown that canonical search and matching models cannot generate the observed wage dispersion for the US. They derive a closed form solution of an indicator of wage inequality: the mean-min ratio (Mm , mean wages over minimum wage observed in data). They prove that this same formula stands for models of search (McCall (1970)), matching (Mortensen and Pissarides (1994)) and islands (Lucas and Prescott (1974)). They use this simple formula, plugging in mean job flows, and show that these kinds of models only generate 1/20 of the observed Mm ratio of residual wages.

In the HKV analysis, finding and separation rates are homogeneous across workers. Calibrating these transition rates to the mean values assigns a tiny role to frictions in the determination of wage dispersion. We show that when we calibrate these values to their distribution the role of frictions is enhanced.

HKV also conclude that on-the-job-search with counteroffers models can generate the observed Mm ratio with some reasonable calibration. In Postel-Vinay and Robin (2002) setup, wage dispersion is achieved. Employed workers search on the job for a new wage offer. When they find it, current and potential employers engage in a Bertrand competition to attract the worker. As a result, wage dispersion increases. Papp (2009), using a calibrated model based on Postel-Vinay and Robin (2002) and Cahuc et al. (2006), argues that on the job search with counteroffers can replicate all the wage dispersion.

It has to be said that these kinds of models rest on the commitment of the firm about future wages. In other words, firms maintain and do not renegotiate the wage agreement with the worker even when the new offer is no longer available. Additionally, this explanation has been discussed in the literature (for example HKV), arguing that this can be the case for some labor markets but it is still on doubt that it can be considered the main source of wage dispersion for the typical worker (see Moscarini (2004) for a formal argument).

An interesting related work is Kambourov and Manovskii (2004) in which wage dispersion can be generated by occupation-specific human capital accumulation. They use an island model, where the islands are the occupations, and they introduce an occupation-specific productivity shock to explain the transition of workers between them. The paper shows that if this idiosyncratic productivity shock were to increase its variance and decrease its persistence, then the model can explain both the rise in wage dispersion and the increase in occupational mobility from the 70s to the 90s.

A similar approach is the one of Violante (2002), in which vintage capital is analyzed. In this case, workers face different productivities according to the age of the machine

that they match with. Changing to other (more productive) machine generates a loss of human capital. Thus, turnover is limited and differences in wages coexists.

The present work differs with Kambourov and Manovskii (2004) and Violante (2002) in that they do not model search process when unemployed and they argue that all the rise in wage dispersion is due to a problem of reallocation of workers between different productive sectors. In other words, the wage differences arise because of heterogeneity in productivity across jobs, while what we try to address is the luck component of wage dispersion.² It also differs from the models of on the job search with counteroffers because of the mechanism behind the wage dispersion: Cahuc et al. (2006) do model search process, but their emphasis is on on-the-job search and not on the endogenous differences in the finding rates across workers. In our view, the heterogeneity that affect unemployment risk is intimately related to the one that implies wage dispersion.

Furthermore, these papers compute wage dispersion as the differences between wages across workers without controlling for productivity of the firm or human capital or any other observed variable such as experience or tenure.

Thus, the contribution of this paper is twofold. First, it emphasizes that dispersion in the incidence of search friction among workers is both empirically relevant and theoretically important. Second, it reassesses the degree of frictional wage dispersion in the context of search models, concluding that the role of luck in determining wages can be predominant.

In the Section 2 some empirical facts and estimations of finding and separation rates are presented. We show that there are important differences in unemployment risk across workers. Furthermore, we present alternative measures of the wage dispersion and of its increase between decades for the US. In Section 3 we analyze the effects of heterogeneity in finding and separation rates on wage inequality using the simple search model framework and including fixed heterogeneity between workers. In Section 4 we make use of the LS model, extended to include endogenous separation rate, and show that this heterogeneity can be accounted with a model in which human capital is accumulated while working and depreciated while unemployed. In Section 5 we present and discuss some alternative extensions to the model. Final section concludes.

2 Some empirical facts

In this section we will present some evidence related to the main forces at work in the model. In particular, we will show some indicators of the heterogeneity in unemployment risk and in wages. We will first present our estimations of lifetime inequality in unemployment risk, using long panel of workers, and review some evidence about heterogeneity in finding and separation rates and about the variance in unemployment duration. Secondly, we will show estimations about wage dispersion and its evolution in the last decades in the US. These changes in wage inequality went along with several

²The distinction is important, given that data shows that wage dispersion is substantial while controlling for differences in productivities or fixed effects of firms.

relevant changes in the US labor market. Part of the section is devoted to present those facts that are related to the effects that can be analyzed by the model at hand. We will concentrate throughout the section in the results for male workers (from 25 to 65 years old), and indicate appropriately when results are for other population group.

2.1 Evidence on inequality in unemployment risk

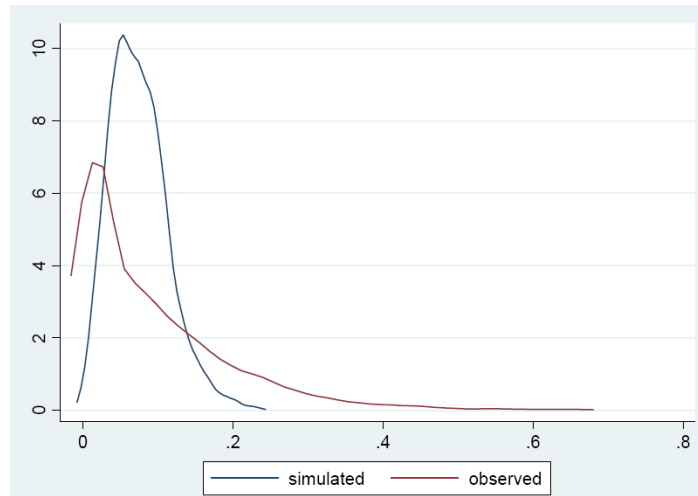
2.1.1 Lifetime unemployment risk

Unemployment risk is usually defined as the probability of employed workers of being in unemployment in some specific future period. In this case, we report the unemployment probability for the whole working life, regardless of the current state.

For doing so, we operationalize the concept by considering the proportion of periods spent in unemployment during life. In this case, we have an estimation of the unemployment risk for every worker given their initial conditions.

We take male workers from the NLSY, and consider the observations (years) in which they are older than 23 years and they declare to be active in the week of the survey. For this observations for each worker we compute the weeks at employment. Then we add them up for each worker and compute the proportion of weeks without a job that these workers during all the observed years. We then concentrate on those workers with 10 or more annual observations and compute the distribution of the proportion of weeks spent without a job.

Figure 1: Distribution of the proportion of lifetime weeks without a job



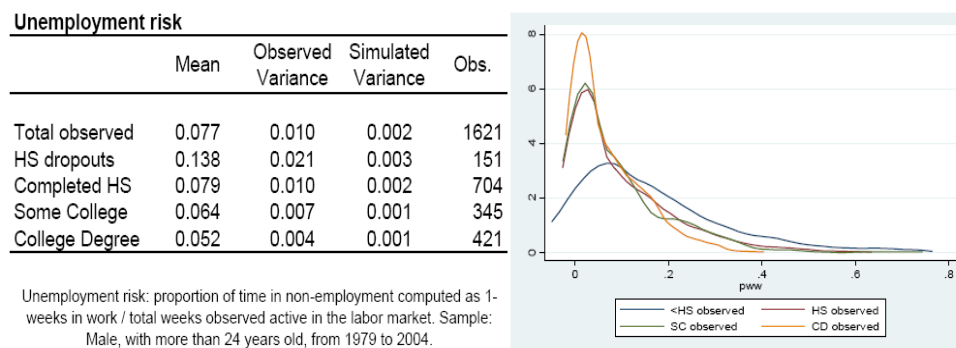
NLSY, 1979-02, men 24 years or more of age with labor market attachment (10 or more years of activity). Weeks without a job over total weeks observed. Simulated distribution stands for constant finding and separation rates.

This indicator is approximately the proportion of weeks spent at unemployment, because these are prime-aged males (for which the activity rate is very high) and because we are skipping those observations in which the worker declared not being active.

On the whole, unemployment risk, defined as the proportion of time spent without a job, present a lot of variance and skewness. While the mean is 7.7%, the median is 4%. The first 10% of workers had spent all the observed periods with a job, while there is another 10% of the workers with more than 21% of the time without a job. (See Figure 1).

This distribution shows a high heterogeneity in unemployment risk and transition rates. To show this, we construct a simulation in which we use constant finding and separation rates to provide a comparison with the observed distribution of the proportion of time without a job. The result of the simulation is a less skewed distribution, with roughly the same mean but with much less variance (one sixth of the observed one).

Figure 2: Distribution of the proportion of lifetime weeks without a job by education



Notes: Men 24 years or more of age with labor market attachment (10 or more years of activity) by educational level. Simulations by education base on constant finding and separation rates that match the mean of the proportion of time without a job. Source: NLSY, 1979-02.

This result is maintained if we concentrate in workers with a given education. In this exercise, we see that the unemployment risk is higher and more dispersed for the low educated group (High School dropouts). But even for the high skilled workers (with completed College), the observed variance is four times the simulated one. (See Figure 2)

From this exercise we show that lifetime unemployment risk is very different between workers, and that many of this difference is highly persistent.

Another way of analyzing the heterogeneity in unemployment risk is to see whether the finding and separation rates (the two components of becoming unemployed in the

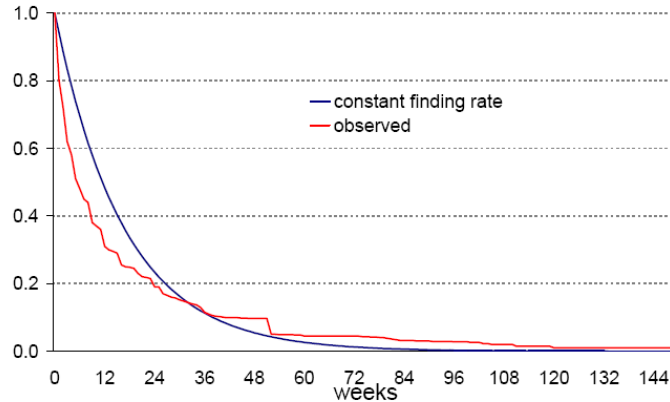
future) are different between workers. We go for this in what follows.

2.1.2 Finding rate

A main issue for the approach of this paper is the heterogeneity in the finding and separation rates across workers. In a first step, we show this issue by analyzing the profile of finding rates in unemployment duration. The literature frequently found that finding rate is decreasing with duration. This can be driven by duration dependence (finding rate for each worker is lower the longer is the spell), or because of fixed heterogeneity (those workers with higher exit rates from unemployment leave the unemployed population quicker, generating a reduction of mean hazard). Both effects are sources of dispersion in the duration of unemployment spells.

The results about finding rates are based in different sources. For example, Machado et al. (2006) used Displaced Worker Supplement (feb 1988 and 1998) of the CPS to estimate their regressions. This supplement asks about a displacement in the last three years and analyzes transitions after this event. The Figure 2 of their paper show the Kaplan-Meier survival function (see Figure 3). The hazard rates computed with this data shows a decreasing monthly hazard rate from 0.4 to 0.1 in week 22; and to 0.05 after week 53. There are several jumps in the empirical hazard rate.³ In any case, there is a strong reduction of exit rate in the first six months for all workers. A drawback of this estimation is that it is not controlling for any worker characteristic.

Figure 3: Kaplan-Meier survival rate



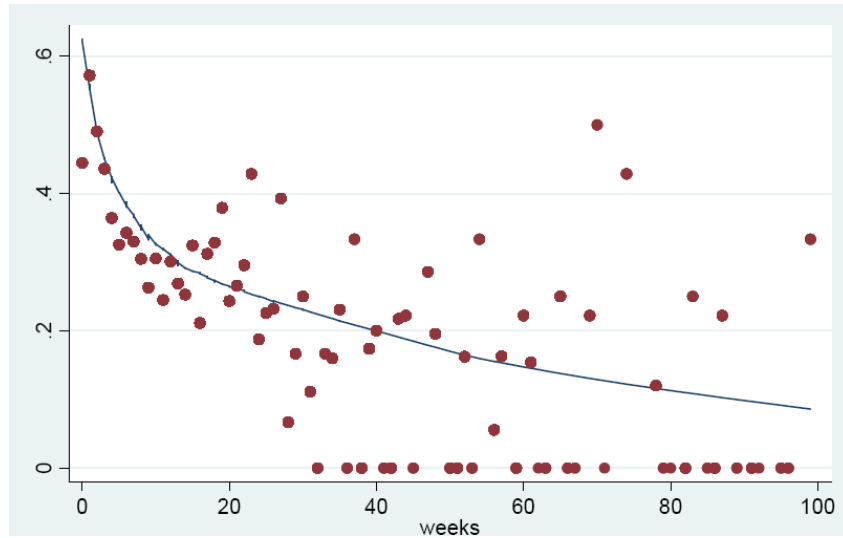
Notes: Machado, Portugal and Guimaraes, 2006, from DWS of CPS, 1988.

³There are some reasons that justify this jumps: (i) retrospective information can generate a rounding in focal points as a year (week 52), what can explain the jumps; (ii) after week 24 only 30% of the sample is present and hazards are much more volatile; (iii) the jumps in weeks 26 and 52 can be also explained by the exhaustion of unemployment benefit.

Meyer (1990) analyzes the hazard rates for covered unemployed and shows that hazard rates are decreasing in the first 20 weeks but then goes up due to exhaustion of unemployment benefit. Katz and Meyer (1990) is instructive also, because it compares recipients with non-eligible workers using PSID data. This paper shows that for UI sample (703 cases), hazard rate is decreasing (from 0.3 to 0.15) until week 20 when it jumps and then continues to go down. For non-UI sample (412 cases) the hazard is simpler and decreases more clearly during the whole analyzed duration: from 0.35 to 0.05 after week 30.

Our own estimations of finding rates are based on the 1997 CPS survey. In this case, prime age males show a decreasing hazard both when analyzed in a nonparametric way and when we allow for controls (educational level, age, marital status, race, whether the workers is new in the labor force and whether he is waiting for a recall). See Figure 4 for a nonparametric approach and Figure 5 for a logistic estimation of the hazard at different durations. On the whole, we estimated the hazard (mean finding rate) for three groups of durations. We found that in this specification, the two-week finding rate is around 20% for the first three months, 13% for the next three months and 9% for those unemployed with more than six months in unemployment.⁴

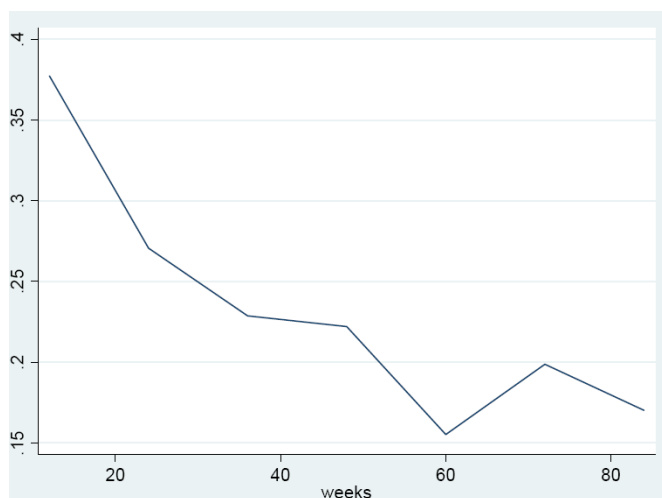
Figure 4: Finding rate-duration profile for males aged between 25 and 64



Notes: Hazard rate from unemployment to employment. Source: CPS, 1997.

⁴The transition probabilities were estimated using the panel dimension of the sample and computing the probability of transiting from unemployment to employment in a given month. A logit model was used to estimate probabilities. The main conclusion is robust to considering only those workers with no recalls, to including specific fixed effects for some durations (those weeks in which unemployment benefit typically ends), and for different duration definitions.

Figure 5: Finding rate - Logit estimates



Notes: Controlled probability of transition from unemployment to employment. Controls are educational dummies, age dummies, race, married, new in labor force, and recalls. Source: CPS, 1997.

There is still debate about the nature of diminishing exit rates from unemployment when duration increases: some studies assess "true" (negative) duration dependence and others explain it by unobserved heterogeneity. To identify both effects, strong assumptions about hazard rate and distribution must be done.

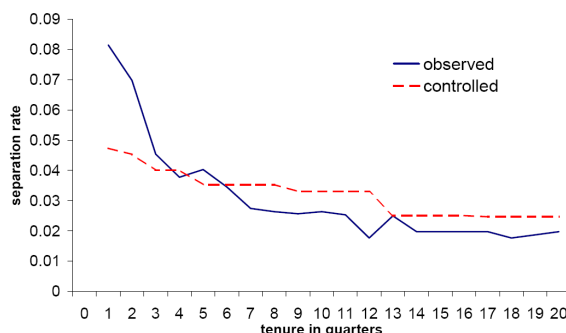
An alternative method was implemented by van den Berg and van Ours (1996). These authors found that for white males unobserved heterogeneity dominates duration dependence effect only in the first month of unemployment, while for longer spells duration dependence prevails. For this group, duration dependence only would make monthly finding rate to decline from 0.52 to 0.34 in the first 4 months. In any case, the heterogeneity in finding rates is substantial, even after controlling for observables.

2.1.3 Separation rate

Separation rate, the other component of the unemployment risk, is also highly heterogeneous and decreasing in tenure. As Farber (1994) shows using NLSY, this rate can be as high as 8% in the first three months of tenure and as low as 2% for highly tenured workers. This decreasing profile is maintained even after controlling for observables, including past labor market transitions of workers. (See Figure 6.)

The separation rate seems to have been rather constant from the sixties. According to Violante (2002) "a large body of work on labor turnover in the US based on various data sets, does not find any significant increase in separation rates (see Wanner and Neumark, 1999 and Neumark, 2000, for an overview)". Also, Farber (2005), using the

Figure 6: Separation rate by duration



Notes: Logit regression controls include sex, married, race, age, education, months of nonemployment, prior mobility histories (prior jobs preceding current job), calendar year, urban. Source: Farber (1994), using NLSY, with labor market attachment, 1979-88.

Displaced Worker Supplement of the CPS does not find any evidence of increase in job loss in the last two decades.

2.1.4 Dispersion of unemployment duration

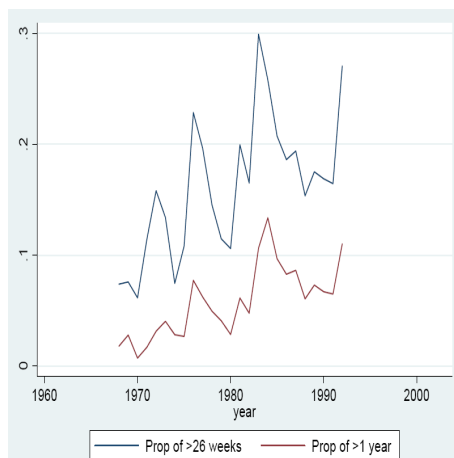
Other connected evidence of the heterogeneity of the finding rates is the distribution of durations. In general, constant and homogeneous finding rates would generate a much less dispersed duration than the one observed. This fact can be seen from the Figure 3 which is based on Machado et al. (2006) computation of survival functions. From this figure, it can be seen that the constant finding rate that generates the same mean than observed duration would generate a much lower dispersion in durations. For example, in the data, the survival probability in the first month is around 60%, while with a constant finding rate it would be around 80%. On the other hand, long durations are more frequent in the data than in the simulated outcomes.

This dispersion in durations has been changing in time. One evidence of this are the results of Machado et al. (2006), that show that between 1988 and 1998 the finding rate for short durations (less than 6 weeks) has increased while for the remaining durations has decreased. That is, short durations are becoming even shorter and long even longer.

Another evidence is the one that comes from the distribution of durations. Firstly, the incidence of long term unemployed has increased substantially since the late sixties to the nineties (see Figure 7). Secondly, the dispersion in observed duration has increased significantly during the same period, an indirect evidence of the evolution of the heterogeneity in finding rates (see Figure 8).

The evidence presented here suggests that unemployment risk is more heterogeneous

Figure 7: Incidence of long term unemployed



Notes: Long term unemployed: proportion of unemployed with duration longer than 1/2 year and 1 year. Source: CPS.

after the nineties than in the sixties. In this period, wage dispersion also increased.

2.2 Evidence on wage dispersion

The main issue that this work intends to explain is the level of residual/frictional wage inequality. Thus, we will provide several estimates and concentrate on the results for the 90s and the late 60s to account for both the level and the rise in wage dispersion over this period.

The methods that we survey are regressions of log hourly wages on controls. The estimates differ in the sources they use, the controls they apply and the methods (fixed effects, cell by cell regressions, etc.). Then, wage dispersion is computed as an indicator of inequality applied to the residuals.

HKV, for example, take advantage of the longitudinal information of the PSID and included worker-specific fixed effects. They report their preferred indicator of residual wage dispersion, the *Mp1* ratio (mean wage over first percentile wage), as being around 1.6 in the late 1960s and around 1.9 in the middle 1990s.

The increase in wage dispersion is well documented fact. Recently, Nagypal and Eckstein (2004), using CPS data, showed that the standard deviation of residual wage for men has grown by around 13 percental points (from 0.44 to 0.57) for men between 1971 and 2002 (see Figure 9). Heathcote et al. (2009), analyzing the period 1967-2006 using the March Current Population Survey (CPS), the Panel Study of Income Dynamics (PSID), and the Consumer Expenditure Survey (CEX), find a substantial increase in income and consumption inequality. Their measure of residual wage inequality for men is higher, and they report an increment of 13 percental points (standard deviation of

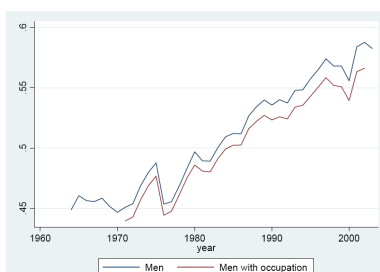
Figure 8: Evolution of the dispersion in unemployment duration



Notes: Standard Deviation of log duration of unemployment.
Source: CPS, 1968 to 1992.

residuals rise from around 0.47 to around 0.6 using CPS). The rise in standard deviation of log wages without controlling for observables increased 18 points in the same period. Gould (2002) computes the residual wage dispersion within narrowly defined workers: white, male, non farm and non-self-employed workers between 25 and 49 years old. He finds a rise from 0.14 (1970) to 0.22 (1988) according to march CPS supplement. This is similar in different sectors and occupations. According to Lee and Wolpin (2006), standard deviation of residual log wages increased from 0.4 to 0.5 from 1968-1974 to 1995-2000 using CPS. Kambourov and Manovskii (2004) compute the same increment using PSID and controlling for occupation-specific tenure (standard deviation increases from around 0.42 in 1970-73 to 0.55 in 1996-96).

Figure 9: Wage dispersion: sd of regression residuals



Notes: Standard deviation of residuals of log hourly wages on observables. Source: CPS, Eckstein & Nagypal (2004).

2.3 Returns to human capital

This rise in residual wage dispersion coexists with increasing returns to human capital, such as education, experience and tenure. For example, Topel (1997) estimates that college wage premium rose from 50 percent in the late 1970s to 80 percent in early 1990s; and that wage premium for experienced workers rose steadily from 30 percent in the late 1960s to 55 percent in early 1980s. Nagypal and Eckstein (2004), Heathcote et al. (2009) and Katz and Autor (1999) also report a similar increments. The relationship between human capital returns and wage dispersion has been emphasized in the literature, for example by Lee and Wolpin (2006), Topel (1997) and Juhn et al. (1993).

There is a somewhat more restricted evidence on increases in returns to tenure specifically. Altonji and Williams (2005), using PSID, estimate a 41% increase in 10 year return to tenure from 1975-1982 to 1988-2001. Their 10-year returns increase from 11% to 15% while the 30-year returns changed from 45% to 41%. On the other hand, Violante (2002), computes the increase in wage growth for stayers from PSID data. All the different definitions of stayers and workers show a significant increase, from around 3% to 5% of annual growth.

An important issue for the human capital process in the life cycle is the wage loss that workers experiment after a separation. Many authors have documented the relevance of wage loss at displacement. For example Jacobson et al. (1993), using administrative data from early and mid 80's for Pennsylvania, estimate wage loss at displacement and find that high-tenure workers separating from distressed firms suffer long-term income losses averaging 25%. Topel (1991) find similar results using CPS data from 1984 to 1986. Again, the mean wage loss is 13.5% and goes from 9.5% in the case of 0-5 years of tenure to 44% for high tenured workers (with more than 21 years). (See Table 1.)

Table 1: Wage loss upon displacement

Wage changes of displaced workers by years of prior job seniority
January CPS, 1984 and 1986

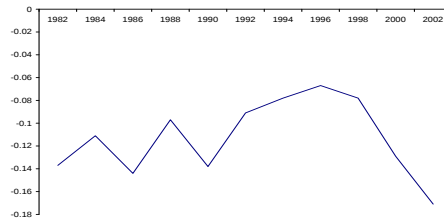
	Years of seniority in prior job				Total
	0-5	6-10	11-20	21+	
Average change in log weekly wage	-0.095 (0.010)	-0.223 (0.021)	-0.282 (0.026)	-0.439 (0.071)	-0.135 (0.009)
Percentage displaced by plant closing	0.352 (0.008)	0.463 (0.021)	0.528 (0.026)	0.750 (0.043)	0.390 (0.007)
Weeks unemployed since displacement	18.69 (0.413)	24.54 (1.202)	26.66 (1.536)	31.79 (3.288)	20.41 (0.385)

Note - Estimates refer to male respondents between the ages of 20 and 60. Sample size is 4367. Nominal data are deflated by GNP price deflator for consumption expenditure. Figures in parentheses are standard errors.

Violante (2002), compute different estimates of wage losses upon displacement from PSID. On the whole find that from 1970-1980 to 1981-1991 wage loss has worsened in 10 percental points. On the other hand, Farber (2005), using Displaced Worker

Supplement of the CPS from 1984 to 2002 does not find any trend in wage loss. His preferred estimation is a difference-in-difference estimation that is around 17% on the whole period. (See Figure 10.)

Figure 10: Evolution of wage loss upon displacement



Notes: Difference in difference estimations of wage loss from 1981 to 2003. Source: Faber (2005) on DWS from CPS, 1981 to 2003.

3 Wage dispersion in basic search models

We now turn to the analysis of wage dispersion and unemployment risk using a simple search model. We will first follow HKV closely and then show how fixed heterogeneity in unemployment risk can generate higher wage dispersion.

3.1 Homogeneous transition rates

HKV have shown that basic search models cannot generate the observed wage dispersion. They base on a particular measure of dispersion, the mean-minimum ratio of wages. They show that search models, properly calibrated, generate a ratio that is 20 times lower than the observed one.

They base on a standard search model in which unemployed workers have a given income flow b and face an exogenous probability (λ) of having a random wage offer drawn from the distribution $F(w)$ which workers have to accept or reject; employed workers earn wage income and face an exogenous probability of being fired (δ). Then, the Bellman equations of being unemployed and employed are:

$$\begin{aligned} rU &= b + \lambda \int \max\{W(x) - U, 0\} dF(x) \\ rW(w) &= w + \delta[U - W(w)] \end{aligned}$$

This problem can be solved using a reservation wage policy, that is, setting a wage w^* above which any wage offer is accepted, characterized by

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

The value while employed of receiving the reservation wage is:

$$rW(w^*) = w^*$$

while the value while unemployed is:

$$rU = b + \lambda \int_{w^*} [W(x) - U] dF(x)$$

Then, replacing $W(x) = (w + \delta U)/(r + \delta)$ and integrating yields:

$$w^* = \bar{w}\rho + \frac{\lambda^*}{r + \delta}(\bar{w} - w^*) \quad (1)$$

where $\lambda^* = \lambda[1 - F(w^*)]$ is the finding rate and ρ is the replacement rate. Then, the mean-min ratio can be directly derived:

$$Mm = \bar{w}/w^* = \frac{\frac{\lambda^*}{r+\delta} + 1}{\frac{\lambda^*}{r+\delta} + \rho} \quad (2)$$

This formula stands for this type of McCall search model, and HKV show that analogous expressions stands for islands model and matching models. Importantly, Mm ratio is independent of the wage offer distribution. In this case, then, wage dispersion (Mm ratio) can be calculated only knowing the exit rate from unemployment, the separation rate, the interest rate and the value of unemployment utility flows relative to mean wages. We compute the formula by calibrating it to monthly mean rates: $r = 0.0041$, $\delta = 0.013$, $\lambda = 0.18$, $\rho = 0.4$. Then, $Mm = 1.048$. While comparing this statistic with the one computed in the data, around 1.9, one can conclude that the dispersion is 20 times larger than one generated by the model.⁵

3.2 Fixed heterogeneity

In the HKV exercise, the mean finding and separation rates are used. Nevertheless, we have shown that these rates are not constant. We will explore, then, the effects of including some heterogeneity in finding and separation rates on the wage dispersion generated by the model.

⁵Our calibration slightly differs from the original paper to be consistent with our own calibration of the complete LS model. HKV compute a 1.03 Mm ratio and compare it to their empirical counterpart of 1.7.

Lets assume that there are two different type of workers that are characterized by their wage offer probability, their separation rate and their utility while employed. Given that in this example these differences are fixed, we can solve their reservation wage problem in the same way as before, to get:

$$\begin{aligned} w_0^* &= \bar{w}_0 \hat{\rho}_0 + \frac{\lambda_0^*}{r + \delta_0} (\bar{w}_0 - w_0^*) \\ w_1^* &= \bar{w}_1 \hat{\rho}_1 + \frac{\lambda_1^*}{r + \delta_1} (\bar{w}_1 - w_1^*) \end{aligned}$$

where $\hat{\rho} = b_i/\bar{w}_i$ is a shortcut (the implicit assumption in here is that replacement rates are the same for both groups. This implies:

$$Mm_i = \frac{\frac{\lambda_i^*}{r + \delta_i} + 1}{\frac{\lambda_i^*}{r + \delta_i} + \hat{\rho}_i}$$

To calculate the aggregate Mm statistic we should determine overall mean wage ($\bar{w}$) and compute $\bar{w}/w_1^*$. To this end, we need to solve for w_1^* , $\bar{w}_0$ and $\bar{w}_1$ separately. But these values depend on the wage offer distribution and its parameters.⁶

We particularize the analysis to the uniform distribution, for which we show that aggregate Mm ratio does not depend on the parameters (upper and lower bound of the distribution). To see this, we use the following property about the mean wage: $\bar{w}_i = \frac{u + w_i^*}{2}$, provided that $w_i^* \geq l$, where l and u are the upper and lower bounds of uniform distribution respectively. Then, the equation (1) applied to the uniform distribution yields

$$w_i^* = \frac{\hat{\rho}_i(u + w_i^*)}{2} + \frac{\lambda_i^*}{2(r + \delta_i)}(u - w_i^*)$$

Then, solving for the reservation wage,

$$w_i^* = u \frac{\hat{\rho}_i r + \hat{\rho}_i \delta_i + \lambda_i^*}{2r + 2\delta_i - \hat{\rho}_i r - \hat{\rho}_i \delta_i + \lambda_i^*}$$

what implies that the ratio $\frac{w_0}{w_1}$ is independent of the parameters of the distribution (in particular, of u). Then, it is direct to show that the aggregate Mm ratio has a closed form solution:

$$Mm = \alpha_e Mm_0 \frac{w_0^*}{w_1^*} + (1 - \alpha_e) Mm_1$$

where α_e is the type 0 proportion of employed workers and Mm_i values are determined by equation (2). Then, the wage dispersion in the case of uniform wage offers depends

⁶For example, for a particular calibration a normal distribution would generate an Mm around 1.28, while for a uniform distribution would be 1.1899.

only on the proportion of each type of workers, α_e , of interest rate and on transition rates for each type.

If we set replacement rates to 0.4 and transition rates to roughly reproduce the mean finding and separation rates by duration, then we can assess the effect of unemployment risk heterogeneity on wage dispersion. Table 2 summarizes the results of these exercises. The first column is the homogeneous workers case. The second one includes only finding rate heterogeneity, and shows that Mm ratio increases four times compared to the calibration with homogeneous workers. When separation rate heterogeneity is included, the Mm ratio increases in more than ten times. These results are stronger when replacement ratios are changed, including a higher replacement ratio for type 0 worker and a lower one for type 1. This is shown in the last column in which overall Mm ratio is around 1.8.

Table 2: Effects of fixed heterogeneity in wage dispersion

Heterogeneity	No	Finding	Finding & Replacement	Finding & Separation	Finding, Separation & Replacement
r	0.002	0.002	0.002	0.002	0.002
α	0.500	0.750	0.750	0.900	0.900
λ_0	0.180	0.250	0.270	0.270	0.270
λ_1	0.180	0.070	0.070	0.070	0.070
ρ_0	0.400	0.400	0.500	0.400	0.500
ρ_1	0.400	0.400	0.300	0.400	0.300
δ_0	0.013	0.013	0.013	0.010	0.010
δ_1	0.013	0.013	0.013	0.050	0.050
Mm_0	1.048	1.035	1.027	1.026	1.022
Mm_1	1.048	1.118	1.141	1.344	1.425
Mm	1.048	1.182	1.227	1.623	1.785

These results are driven by two effects. On the first place, Mm ratio of type 1 workers is much higher: this type of workers are more affected by search frictions because they face lower finding and higher separation rates. Then, if we define the degree of search friction as $k = \delta/\lambda$, this type of workers suffers an incidence of search frictions 20 times higher than the type 0 workers.⁷ This generates a much lower reservation wage for type 1 workers and a $Mm_1 = 1.34$ just for them. The second effect is the difference between mean wages: given that reservation wages are so different, so are mean wages. Then, overall mean wages are higher than mean wages of type 1 workers (like 20% in

⁷This definition of the degree or incidence of search friction is similar to one defined by Ridder and van den Berg (2002), which is λ_e/δ . In their case, the formula includes the average number of wage offers that an employed worker would receive during a spell of employment. In our case, is related to unemployment risk. Lifetime unemployment risk for each type, in this case, would be $u = \frac{k}{1+k}$.

the example), increasing aggregate Mm ratio to 1.62.

These simple exercises shows that heterogeneity in transition rates can explain almost all of the residual wage dispersion. Intuitively, a lower job offer probability imply a reduction in reservation wages because waiting for another wage draw is more costly. This reduces the value of being unemployed and, thus, the reservation wage. At the same time, a higher displacement rate reduces the value of being employed: jobs last less periods and thus finding a higher wage is less worthy. On the whole, reservations wage is lower the higher the incidence of search friction, k . Heterogeneity in unemployment risk, additionally, generates different mean expected wages between workers.

3.3 Heterogeneity with duration dependence

We now turn to the issue of duration dependence in transition rates. We derive the formulas for wage dispersion (the mean over minimum wage or Mm ratio) when there are two types of workers, but transitions occur between these two types. Each type is characterized by the level of transition rates and the replacement rate. The overall Mm ratio depends only these parameters when wage offers are drawn from a uniform distribution.

We will consider the case in which a worker of type 0 has a lower unemployment risk (higher finding rate and lower separation rate) compared to type 1. Additionally, a type 0 worker has a probability ϕ of becoming a type 1 worker when unemployed, and a type 1 worker has a probability Ψ of becoming a type 0 worker when employed. This type of transition resembles the negative duration dependence in finding and separation rates. Then, the fall of hazard rates by duration is both driven by fixed heterogeneity and duration dependence in this setup. This is the main advantage: it seem to be more convenient for comparing with data and for calibration.

This example also relates to a situation in which the ability to find and keep a job is improved with employment (experience) and worsened with unemployment. This process can be related to the effect of the human capital accumulation on transition rates. It leaves aside the direct effect of human capital on income, though, an issue that will be addressed in the full quantitative model.

We assume that workers face two different levels of transition rates, both finding and separation rates. In this case,

$$\begin{aligned} rU_0 &= b_0 + \lambda_0 E[W_0(w) - U_0 | w > w_0^*] + \phi[U_1 - U_0] \\ rU_1 &= b_1 + \lambda_1 E[W_1(w) - U_1 | w > w_1^*] \\ rW_0(w) &= w + \delta_0[U_0 - W_0(w)] \\ rW_1(w) &= w + \delta_1[U_1 - W_1(w)] + \Psi[W_0(w) - W_1(w)] \end{aligned}$$

where U_i is the value of being unemployed of type $i = 1, 2$ worker, W_i is the value of being employed of type i worker, ϕ is the transition from type 0 to type 1, with $\lambda_0 > \lambda_1$, and where Ψ is the transition between type 1 to type 0 worker when employed, with $\delta_0 < \delta_1$. Note that λ is the finding rate (not wage offer rate). Note also that quitting could be convenient when an employed worker of type 1 transit (improves) to a type 0 case. In this example we avoid the quitting possibility.

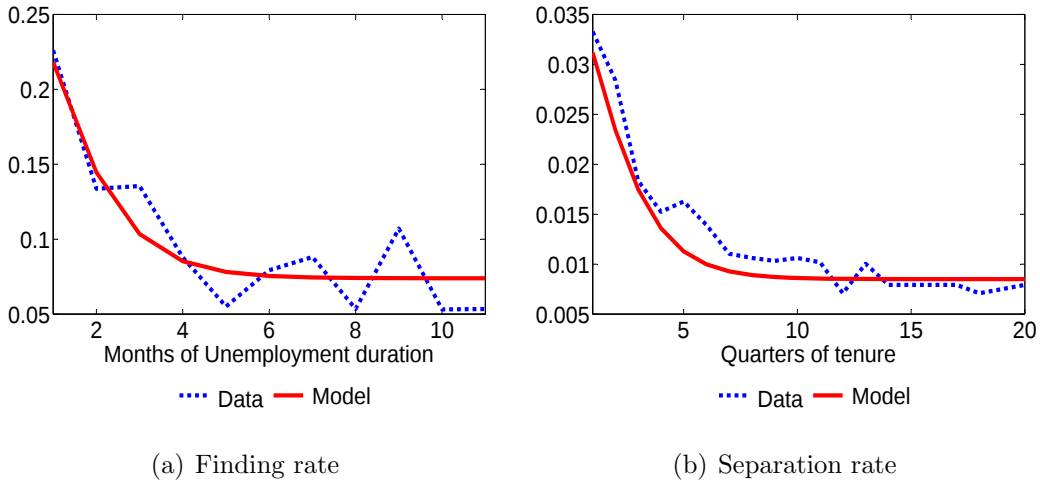
By solving the model, the Mm ratio turns out to be dependent only on parameters in the case of a uniform distribution. In particular, for that distribution the indicator can be computed using the following equation:

$$Mm = \frac{1-\alpha_0}{2} + \frac{\alpha_0}{2} w_0^*/w_1^* + \frac{1}{2} u/w_1^*$$

where α_0 is the proportion of type 0 employed workers (which depends only on transition rates). It turns out that both u/w_1^* and w_0^*/w_1^* depend only on parameters (transition rates, replacement rates and interest rate). We omit derivations and formulas, and leave them to the Appendix.

For the calibration we considered the fact that the transition rates $(\lambda_i, \delta_i, \phi, \Psi)$ generate a stationary distribution of workers. We computed the stationary proportion of workers in each state (employed and unemployed) and each type (type 0 and type 1) using the transition matrix implied by these rates. We finally used the finding and separation rates presented before and calibrate λ_i , δ_i , ϕ and ψ to finding rates by unemployment duration and separation rates by tenure. Finding and separation rates from simulation and data are shown in Figure 11.

Figure 11: Calibration



When calibrating transition rates and setting replacement ratios to 40%, we get that the Mm ratio increases to 2.1. In this case, type 0 worker would perceive the probability of becoming a type 1 worker and would reduce his reservation wage down to avoid being the higher unemployment risk type.

In this setup there is an additional incentive to accept jobs for the lower unemployment risk worker: to avoid becoming a high unemployment risk type of worker. Additionally, accepting a job is not only valuable for the fact that it provides a wage but because it can improve transition rates, i.e. high risk workers can improve their

situation by accepting a low wage job. These aspects reduce reservation wages of both types of workers.

4 A model of search with human capital accumulation

Up to now the relationship between wage dispersion and transition rates dispersion has been addressed in a simple context in which these differences are exogenous. The objective of this section is to show how these differences in finding and separation rates can arise endogenously due to the incentives implied by human capital accumulation.

To this end, we borrow from Ljungqvist and Sargent (1998) model. In this model human capital accumulates on the job. Then, human capital increases while being employed and decreases (it depreciates) while being unemployed. Furthermore, there is a loss of human capital at layoff, that accounts for the specificity of on the job learning.

Human capital accumulation generates important changes in incentives in the search process. Firstly, jobs are now more valuable for the unemployed, because not only they provide for wage income but also they help to improve human capital level. This effect imply a reduction in reservation wage for unemployed workers with low human capital. Secondly, being unemployed is a particularly damaging period because of the progressive depreciation of human capital that it entails. Thus, an unemployed worker would try to reduce its length. Lastly, the human capital loss at displacement can be very high, what induces skilled workers to accept a wage cut to avoid layoff.⁸

This kind of process can be justified by the evolution of wages among workers. In particular, as documented in Section 2 wages tend to increase with tenure and with labor market experience and reemployment wages tend to be lower than pre-unemployment wages.

The setup of the model is as follows. Workers exhibit a given death rate, α , and have a discount factor, β . While unemployed, the worker perceives an instant utility value b , searches for a job at a cost cs and has a probability of receiving a wage offer $\pi(s)$, that depends on his search effort, s . They also face a shock with arrival probability of μ_u upon which human capital depreciates. On the other hand, while employed, the worker receives an income flow of wh , where h is his human capital level, suffers an exogenous shock with arrival probability of δ in which case he is laid off. When working, the worker will increase human capital with probability μ_e . Finally, at layoff, a proportion of human capital is lost. This proportion is governed by the transition probabilities $\mu_l(h, h')$.

We will extend this model by introducing an additional shock, δ_e , which is the arrival probability of a job-specific shock. This shock implies that wage is redrawn from its distribution $F(w)$. In this case, the worker has to decide if he accepts the new wage

⁸This last effect is not present in the original LS model and is a consequence of endogenizing the separation rate. This generates heterogeneity in separation probabilities.

offer or to be fired.⁹

We denote $U(h)$ the value of being unemployed with human capital level h , while $W(w, h)$ is the value of being employed with human capital level h and wage w . Then, the Bellman equation for the unemployed is

$$U(h) = \max_s \left\{ b - cs + \beta(1 - \alpha)(1 - \mu_u) \left[(1 - \pi(s))U(h) + \pi(s) \int \max\{W(w, h), U(h)\} dF(w) \right] + \beta(1 - \alpha)\mu_u \left[(1 - \pi(s))U(h - \Delta h) + \pi(s) \int \max\{W(w, h - \Delta h), U(h - \Delta h)\} dF(w) \right] \right\}$$

while the value of being unemployed is:

$$W(w, h) = \max \left\{ wh + \beta(1 - \alpha)(1 - \delta)(1 - \delta_e)[(1 - \mu_e)W(w, h) + \mu_e W(w, h + \Delta h)] + \beta(1 - \alpha)(1 - \delta)\delta_e \int \max\{(1 - \mu_e)W(w', h) + \mu_e W(w', h + \Delta h), \sum \mu_l(h, h')U(h')\} dF(w') + \beta(1 - \alpha)\delta \sum \mu_l(h, h')U(h') , \sum \mu_l(h, h')U(h') \right\}$$

The policy functions that solve the Bellman equations are the search intensity, $s(h)$, the reservation wage while unemployed, $w_u(h)$, and a reservation wage while employed, $w_e(h)$. Additionally, the value while employed implies also that the worker can decide in each period to quit if the value of being unemployed is higher than while being employed (the existence of human capital loss at displacement will prevent him to do so, in practice).

In the simulation of this model, we assume that workers begin their working life with the lowest level of human capital.

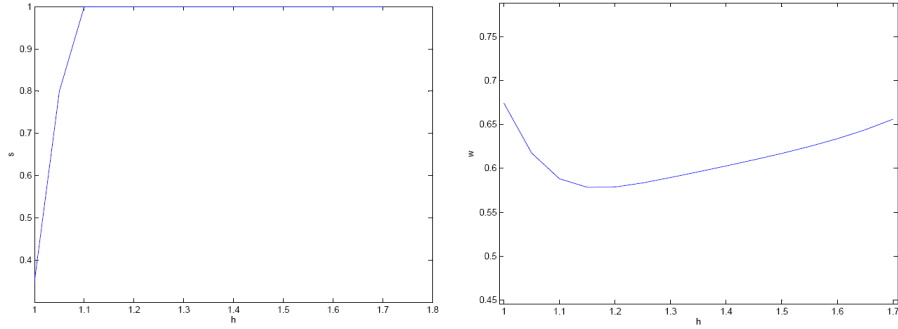
4.1 Policy functions

We now turn to the characterization of the policy functions from numerical solution of the model.

The search intensity and the reservation wage while unemployed are shown in Figure 12. These two policy functions are related to the incentives to search by human capital level. In particular, the search intensity is low for unexperienced workers and increasing in the first part of the domain, reaching its maximum quickly.

⁹One can think of this shock as the probability that the job face an adverse productivity shock after which wages are revised.

Figure 12: Policy functions: Search effort and reservation wage



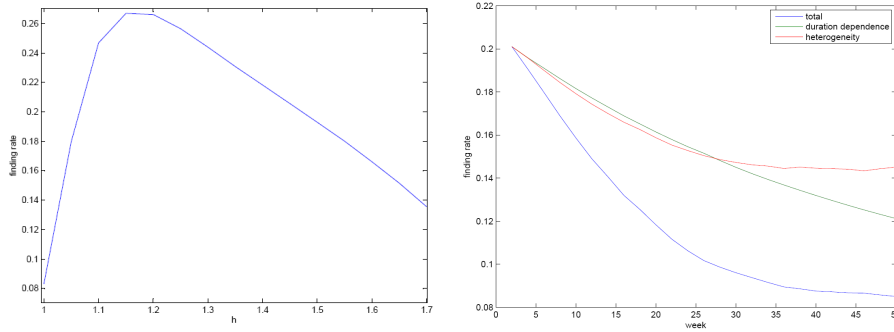
Notes: Policy functions resulting from solving the quantitative model of Section 4.

The reservation wage is not decreasing in human capital level, as a simple model would tell, but U-shaped. In a simple model, low skilled workers would require a higher reservation wage given that the utility value while unemployed is fixed and income is increasing with h . But the process of accumulation of skills generates additional incentives that generate a very different outcome for which both the lower and the highest skilled have a relatively high reservation wages. Workers with the lowest level of human capital have nothing to loose in terms of depreciation of human capital if unemployment spell is extended. For this reason, these workers have less incentives to find a new job quickly, lowering their search effort and increasing their reservation wage. On the other hand, the unemployed workers with the highest level of human capital are not very much affected by a decrease in skills, because they could be recovered relatively quickly while employed, but have much to gain with a better wage offer (higher h implies a more important income difference for a given percental change in w). On other words, they prefer to keep looking for a higher wage even if they face a probability of skill depreciation. This is the reason of their high search effort (relative to low skilled) and high reservation wages. Finally, the workers with intermediate levels of human capital are the ones for which the incentives to get a job are highest: loss of skills affect them and they have a lot to gain because of learning on the job.

Human capital accumulation process affect not only the shape of reservation wage and search effort, but also in their level. Indeed, in the model the value of being employed goes beyond the wage level and includes the value of accumulating human capital, which is an important source of gain. This effect lowers reservation wage and is more important for the low skilled workers. Conversely, the value of being unemployed is reduced by the effect of the loss of skills. This effect is more important for the highly skilled workers. For the intermediate levels of human capital, both effects coexist and reinforce each other. On the whole, the incentives of accepting a job are enhanced.

Finding rate is plotted in Figure 13. It inherits the shape of search effort and reservation wages, given that is $\pi(s(h))[1 - F(w_u(h))]$. Then, the finding rate has an inverted U shape as a function of h . If all workers entering unemployment were in the peak of this finding rate profile, that is with intermediate human capital, then the observed finding rate would be decreasing, because of the progressive depreciation of human capital for the unemployed workers.

Figure 13: Finding rate by human capital level and by duration of spell



Notes: Left hand side graph shows the finding rate as a function of human capital that arise from policy functions plot

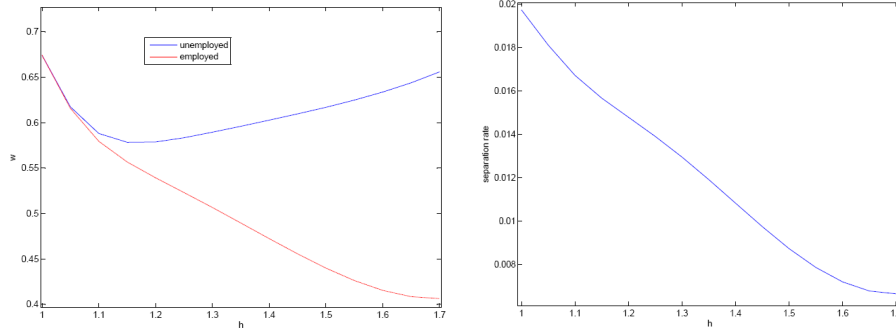
In fact, the simulated finding rate is decreasing in duration because of two effects. Firstly, the workers with high hazard rate at the beginning goes out from the unemployment population quicker, leaving only the lower hazard rate types for longer durations. This effect is similar to that caused by unobserved heterogeneity in a duration model. Secondly, after some level of human capital, finding rates tend to decline because of its reduction when human capital decreases. This can be associated to the duration effect of a decreasing underlying hazard. In the model, as in the data, these two effects are of similar importance in the first four months (as observed by van den Berg and van Ours (1996) for male workers), but after six months the duration dependence effect is much stronger.

Thus, the human capital accumulation process generates an important and intuitive source of heterogeneity in hazard rates that are intimately related to the ones observed in the data, for which duration dependence and unobserved heterogeneity coexists. Additionally, it offers a simple and direct framework in which dispersion in hazard rates and in wages are intimately related.

The reservation wage while employed, $w_e(h)$, is different to the reservation wage while unemployed, $w_u(h)$, because of the existence of human capital loss at displacement. Both reservation wages are equal for those workers for which there is no loss at displacement, i.e. the lowest human capital workers ($w_e(\underline{h}) = w_u(\underline{h})$). But for higher skilled workers, this difference increases. The intuition behind this result is that high

skilled workers accept temporary wage cuts in order to avoid losing human capital (a more persistent damage). This shape of reservation wages implies that separation rates are endogenous and heterogeneous across workers: most of the job-specific shocks that occur to low skilled workers end in separation, but only a few of idiosyncratic shocks end up in a layoff for high skilled workers. (See Figure 14.)

Figure 14: Policy functions: reservation wage while employed and separation rate



Notes: Left hand side graph shows the policy functions of reservation wage while unemployed and employed as a function of human capital. Right hand side graph is the separation rate as a function of human capital that is compatible with the reservation wage while employed.

4.2 Quantitative results

In this section we present the quantitative results for the model. Parameter values are set to be coherent with some moments of the data, such as the decreasing finding rate with duration, the decreasing separation rate with tenure, the existence of wage loss at displacement that is increasing with tenure, and the increase in wages with tenure on the same job. Table 3 summarizes the calibration. We consider that each period lasts two weeks.

This numerical exercise does well in generating some patterns of the data, as Table 4 shows. In particular, finding and separation rates are decreasing in duration, wages increase by tenure and wage loss is more severe for higher tenured workers. Nevertheless, some values differ. For example, the wage loss at displacement is lower than the one observed (even in the exogenous separation case), what is implying that the calibration is not overstating the loss at displacement. In the same way, separation rate profile is much flatter than the one observed.

Table 3: Calibration: parameter values

Parameter	Definition	Value
α	Death rate	0.002
β	Discount factor	0.9985
$F(w)$	Wage offer distribution	log normal
δ	Exogenous layoff probability	0.002
δ_e	Job specific shock probability	0.02
$\pi(s) = s^\eta$	Wage offer probability	$\eta = 0.3$ $s \in [0, 1]$
b	Utility while unemployed	0.55
c	Search cost	0.3
μ_u	Human capital depreciation probability	0.2
μ_e	Human capital accumulation probability	0.03
$\mu_l(h, h'), h' < h$	Human capital loss at displacement	0.05

All rates are at two-week level. Wage distribution $F(w)$ is a log normal truncated such that $w \in [0.3, 1]$, where the mean of $w \simeq 0.52$ and the variance of the log normal is 0.07. Human capital $h \in [1, 1.7]$ implemented as a vector of 15 positions.

4.3 Unemployment risks and wage dispersion

This model generates much more inequality in wages than the canonical search model. In fact, considering the Mm indicator, the model does pretty well, reaching a value of 1.66, close to the Mm level of the data of 1.7, and accounting for the 75% of the residual wage dispersion that we put as a benchmark, which is 1.9. (See Figure 15.)

It also generates dispersion in duration: the standard deviation of log durations is as in the data. It generates much less incidence of long spells, though, with only 6.5% of long term unemployed, while in the data this value is higher than 10%.

Additionally, simulations generate a proportion of periods into unemployment in a 15 year span that is comparable to its distribution in the data.

4.4 The rise in unemployment risk and wage dispersion

This model can account for the wage dispersion. Can this model account for the increase in wage dispersion? Many of the effects that generate wage dispersion in the model are stronger in the 90s than in the 60s. For example, as we have presented in the section 2, human capital returns have increased during these decades, finding rate seems to be steeper and idiosyncratic shocks to wages seem to be more frequent and, to some extent, wage loss at displacement has probably increased.

To analyze this issue, we can test whether the model responds to some of this shocks with an increase in the wage dispersion and in the duration dispersion.

Table 4: Results from quantitative model

	Model HKV	Model Exog. Separation	Model Endog. separation	Data	Source
Finding rate 1-11 weeks	0.184	0.167	0.184	0.200	Estimation for 1997. CPS matched months
Finding rate 12-23 weeks	0.184	0.013	0.127	0.130	Estimation for 1997. CPS matched months
Finding rate 24+ weeks	0.184	0.093	0.089	0.090	Estimation for 1997. CPS matched months
Mean finding	0.184	0.129	0.134	0.180	Estimation for 1997. CPS matched months
MW loss at displacement	0.000	-0.075	-0.026	-0.135	Topel, 1991,
W loss 0-5 years of tenure	0.000	-0.065	-0.024	-0.095	Topel, 1991,
W loss 6-10 years of tenure	0.000	-0.121	-0.088	-0.223	Topel, 1991,
W loss 11-20 years of tenure	0.000	-0.157	-0.114	-0.282	Topel, 1991,
W loss 21y tenure +	0.000	-0.262	.	-0.439	Topel, 1991,
Tenure return 5 years	0.000	0.139	0.103	0.180	Topel, 1991
Tenure return 10 years	0.000	0.255	0.187	0.240	Topel, 1991
Separation rate	0.013	0.013	0.013	0.013	
Separation rate at <3 years of tenure			0.013	0.020	Farber, 1994, Fallick and Fleischman, and Nagypal,
Separation rate at >5 years of tenure			0.010	0.008	

Notes: Comparison between moments generated by the solution and simulation of the quantitative model and the analogous moments estimated through data.

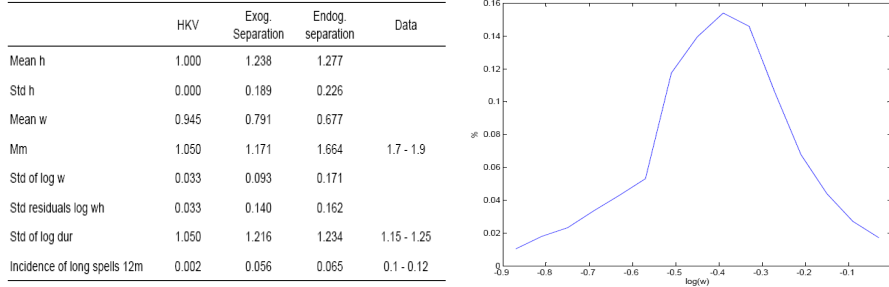
The shocks that we will consider are a decrease in the returns to human capital, changing $\bar{h}$ from 1.7 to 1.5; a decrease in the wage loss at displacement, setting μ_l from 0.05 to 0.01; and a reduction in the probability of a job-specific shock, δ_e , from 0.02 to 0.01. All these are reductions of effects because we depart from the 90s calibration.

When introducing the shock to human capital, the model generates a reduction in Mm ratio of 0.28 (in the data around 0.3) and a reduction in duration dispersion of 0.01 (while in the data is 0.2). The shock to human capital loss at displacement, μ_l , generate important outcomes in finding rates, making them higher and flatter. This affects the results on wage dispersion (that reduces in 0.37) and in the distribution of duration (that reduces 0.11, much closer to the data). The shock to the arrival probability of a job-specific shock, δ_e , generates flatter and lower finding rates, what makes the duration dispersion to increase, while the Mm ratio goes down in 0.17. (See Table 5.)

If we combine the three shocks, the results are finding rates that are flatter, with changes similar as the ones reported in section 2. The impact on wage dispersion is to reduce the Mm ratio to 1.24, that is a change of 0.42, over the 0.3 computed for the data. The impact over the distribution of duration is much lower than in the data, related to the result of the reduction in δ_e .

On the whole, the model performs well when shocks are introduced, matching all the rise in wage dispersion from the 60s to the 90s and some of the reduction in duration

Figure 15: Results from quantitative model: wage dispersion



Notes: Comparison between wage distribution generated by the solution and simulation of the quantitative model and the distribution of residual wages.

dispersion.

5 Extensions to the model

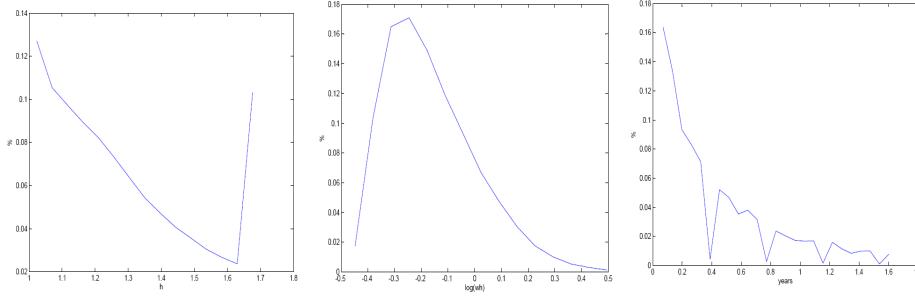
In this section we discuss some extensions to the model. We consider issues that are relevant for introducing additional heterogeneity in search frictions. We first consider the case in which human capital level affects the wage offer arrival rate, as if the firms valued more those workers with high human capital. Secondly, we extend the model to introduce on-the-job search. This extension changes the nature of search frictions in the model: in this case, the degree of search frictions is not only determined by finding and separation rates, but also by job-to-job transition probabilities. Again, all the transition probabilities are related to the human capital level, so that heterogeneity is emphasized by this extension.

We discuss all these extensions to conclude that with them the unemployment risk heterogeneity is enhanced and some of the conclusions are powered.

5.1 Human capital effect on wage offer arrival rate

The reasons for being worried about losing human capital are not only the income while employed but also the probability of having a wage offer. In other words, firms would prefer (other things equal) high human capital workers that are more productive. In a random matching context, for example, firms that meet low skilled worker would probably be tempted to continue to search until finding a more productive worker. Only the matches that generate very high idiosyncratic productivity would generate jobs for low skilled unemployed workers, while high skilled workers would find it more probable to find a job. This result would depend on the human capital distribution

Figure 16: Distributions: human capital, income and duration



Notes: Distribution of human capital, of labor income and of unemployment duration that arise from solving and simulating the quantitative model.

of unemployed workers: if only very few high skilled workers are available, low skilled workers would find it less difficult to find a job; conversely, if an important proportion of high skilled workers are unemployed, then low skilled would be long term or structural unemployed workers.

A kind of reduced form for this effect in the context of this model is to consider that wage offer probabilities depend directly on human capital level in a positive way. If this probability is introduced to the model (for example $\pi(s, h) = f(h)s^\eta$, where $f(h)$ is increasing in h) then the results can be powered. For example, finding rate could be, for certain parameter values, a positive function in human capital (not an inverse U shaped function), what increases the value of being a high skilled worker and what increases the duration dependence while unemployed.

5.2 On the job search

The possibility to search on the job generates important effects on wage dispersion. As a robustness check, we show that our results are even stronger when we include on the job search. In particular, given that a job includes the option value of finding a better job, the reservation wage is reduced. Additionally, there is another counteracting effect, which is that employed workers with low wages search more intensively on the job and change jobs with higher probability. This tend to reduce mass in the lower tail of the distribution of wages. This is especially true for the high skilled workers. Two effects are relevant: on the one hand, high skilled employed workers would accept strong reductions in wages given that they can look for other job avoiding losing their skills; on the other hand, any reduction would be quickly avoided by a job to job transition.

One way to introduce on the job search for the model is to consider that employed workers can search for new jobs at a cost $c(s_e)$, which is an increasing and convex func-

Table 5: Effects of the changes in parameter values

	90s	Change in Human capital	Change in Wage Loss at displacement	Change in Job specific shock	All effects	Change	Change in Data
2week Finding rate 1-11 weeks	0.184	0.171	0.247	0.149	0.181	0.003	0.010
2week Finding rate 12-23 weeks	0.127	0.125	0.190	0.113	0.158	-0.031	-0.010
2week finding rate 24+ weeks	0.089	0.088	0.133	0.078	0.107	-0.019	-0.010
MW loss at displ	-0.026	-0.039	-0.024	-0.059	-0.043	0.017	-0.100
W loss 11-20 y	-0.114	-0.116	0.002	-0.166	-0.046	-0.068	-0.100
Tenure return 10 year	0.187	0.186	0.119	0.233	0.118	0.069	0.040
Mm	1.664	1.379	1.293	1.497	1.243	0.421	0.300
Std of log w	0.171	0.132	0.138	0.125	0.118	0.053	0.130
Std of log dur	1.234	1.225	1.120	1.254	1.189	0.045	0.200
Incidence of long spells 12m	0.065	0.065	0.013	0.095	0.040	0.024	0.070

Notes: Results from the exercise presented in Section 4.4 that intends to reproduce the changes between 1960's and 1990's as a robustness check of the model.

tion¹⁰, and face a wage offer with probability $\pi(s_e)$. The workers decide the reservation wage for a job to job transition. Given that human capital is partly specific to the job, some of it can be destroyed when these transitions occur. This is not known ex ante and has a probability of occurrence of μ_j .

Then, the Bellman equations are:

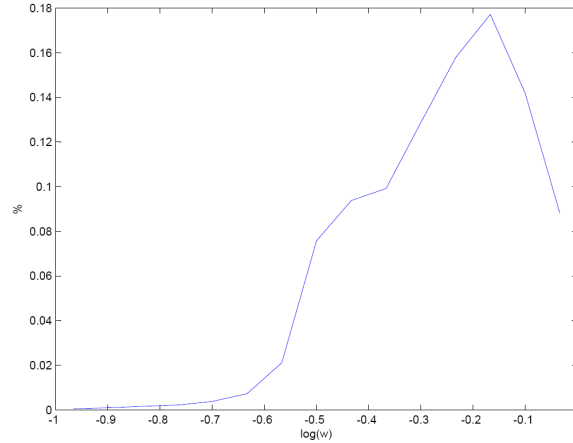
$$\begin{aligned}
 U(h) = \max_s \Big\{ & b - cs \\
 & + \beta(1 - \alpha)(1 - \mu_u) \left[(1 - \pi(s))U(h) + \pi(s) \int \max\{W(w, h), U(h)\} dF(w) \right] \\
 & + \beta(1 - \alpha)\mu_u \left[(1 - \pi(s))U(h - \Delta h) + \pi(s) \int \max\{W(w, h - \Delta h), U(h - \Delta h)\} dF(w) \right] \Big\}
 \end{aligned}$$

¹⁰This shape is justified in the fact that any additional unit of time spent in search is more costly. This is specially true when time is scarce, which seems to be the case for employed workers, and what distinguish them from unemployed searchers.

$$\begin{aligned}
W(w, h) = \max \Bigg\{ & \max_{s_e} \{ wh - c(s_e) \\
& + \beta(1 - \alpha)\pi(s_e) \int \max\{ \sum \mu_j(h, h')W(w', h'), (1 - \mu_e)W(w, h) + \mu_e W(w, h + \Delta h) \} dF(w') \\
& + \beta(1 - \alpha)(1 - \pi(s_e))(1 - \delta)(1 - \delta_e)[(1 - \mu_e)W(w, h) + \mu_e W(w, h + \Delta h)] \\
& + \beta(1 - \alpha)(1 - \pi(s_e))(1 - \delta)\delta_e \int \max\{ (1 - \mu_e)W(w', h) + \mu_e W(w', h + \Delta h), \sum \mu_l(h, h')U(h') \} dF(w') \\
& + \beta(1 - \alpha)(1 - \pi(s_e))\delta \sum \mu_l(h, h')U(h') \Bigg\} \\
& , \sum \mu_l(h, h')U(h') \Bigg\}
\end{aligned}$$

in which we assume that first the worker face wage offers, then can become separated and face a job-specific shock, in that order.

Figure 17: Wage distribution in the model with on-the-job search



In this setup, the decision of the worker includes a search effort while employed, $s_e(w, h)$, and a reservation wage for job to job transition, $w_j(w, h)$. Given that there is a loss of human capital in job-to-job movements, then search effort would not be always positive. The calibration of this extension is based on the fact that only 20% of the workers search on the job (as Fallick and Fleischman (2004) pointed out), that about 20% of the job-to-job transitions imply a reduction of wages ($\mu_j = 0.3$), and that employment to employment transitions represent around 1.65% a month and are decreasing in experience (Nagypal (2006)).

The results are that Mm ratio is increased to more than 2, the dispersion of duration is also higher than the one observed (is 1.47 vs 1.25) and that wage loss at displacement is increased to almost the observed value (even when μ_l in this calibration is 1%). The distribution of wages in this context is highly skewed to the left: the low wages are abandoned rapidly by job to job transitions, while high wages are more populated. (See Figure 17.)

6 Concluding remarks

This paper highlights the importance of heterogeneity in unemployment risk. Heterogeneity in both finding and separation rates is not usually a feature of search models. Nevertheless, it is a fact from the data. First, we show that finding rates are decreasing in duration and that separation rates decrease with tenure. This characteristic, that is maintained after controlling for observables, can be generated by fixed unobserved differences or by duration dependence. In any case, heterogeneity is apparent. We conduct an additional and independent measure of heterogeneity of the incidence in search frictions on workers: the variance of life-time unemployment risk. For computing this statistic, we measure the proportion of periods that workers spend without a job in lifetime. We find that this measure is highly dispersed between workers, and that its distribution cannot be matched by constant finding and separation rates.

We then show how this heterogeneity is crucial for understanding wage dispersion. In particular, when a search model is calibrated using mean transition rates the result is a very compressed wage dispersion. When fixed heterogeneity is used in the calibration, wage dispersion is very high, representing around 70% of the residual wage dispersion. The same occurs when the source of heterogeneity is duration dependence.

In this first approach finding and separation rates are exogenous. The main economic force behind this relationship is that those workers with higher unemployment risk set a lower reservation wage to avoid unemployment. Higher frictions (lower finding rate, higher separation probability) imply a lower reservation wage and higher dispersion in this setup.

We borrow from Ljungqvist and Sargent (1998) model of search with human capital accumulation to endogenize the heterogeneity in finding and separation rates and to account for duration dependence. In this model, *ex ante* identical workers become different in human capital because of their labor market history, given that human capital is accumulated while employed, depreciated while unemployed and lost in a random proportion at the moment of separation. We extend the model with a job-specific shock for introducing endogenous separation.

In the model, differences in finding and separation rates arise because of this human capital accumulation process. In particular, low skilled unemployed workers tend to value jobs not only because of its wage, but also because of the option value of increasing human capital what makes them to accept lower wages. High skilled unemployed workers, conversely, reduce their reservation wage to shorten their unemployment spells and preserve their human capital. For unemployed workers in the middle range of skills, both effects coexist. Finally, high skilled employed workers tend to accept transitory wage cuts just to avoid the human capital loss that occurs in the case of a layoff.

We also argue that these economic forces can be behind the rise in the inequality that occurred in the US from the 60's to the 90's. In fact, human capital accumulation process has changed over these decades: returns to experience are higher, in the 90's. This change coexisted with finding rates that turned to be more heterogeneous in the 90's, increasing duration dependence.

We compute the change in inequality by recalibrating our model to represent US economy in 1960 and find that the change in inequality is similar to the one of the data. Thus, this rise in the heterogeneity of the incidence of search frictions imply an increase in wage dispersion.

On the whole, we have reassessed the importance of frictions on wage dispersion, showing that the canonical search model extended to account for heterogeneity in transition rates (by fixed effects or through human capital accumulation process) can explain almost all the residual wage inequality of the data. On the whole, luck due to frictions would explain much of the total wage dispersion. This conclusion is important for policy design. In particular, for insurance policy: in this setup, unemployment insurance would be especially valuable given the positive probability to spend a high proportion of periods without a job, the substantial income loss due to displacement and the great uncertainty on reemployment wages.

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