

Job Mobility and Earnings Instability

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Abstract

There is still no consensus on the causes of the increase in the variance of transitory earnings (earnings instability) in the US. It is difficult to attribute the rise in instability to job mobility because there is no evidence of a concurrent increase in job turnover or separations. Using an error component model of the covariance structure of earnings on PSID and SIPP data, this paper shows that job mobility and the increase in the variance of wage changes upon job change accounts for a substantial part of the increase in earnings instability. The empirical evidence is consistent with the simulations of a search and matching model where an increase in the variance of productivity shocks increases on-the-job search and earnings instability among job changers while leaving job turnover approximately constant.

Keywords: Earnings instability, On-the-job search, Job mobility, Job turnover, Search and matching.

JEL Classification: J21, J31.

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1 Introduction

The evolution of earnings instability, i.e. the variance of the transitory component of individual earnings, in the US has been well researched since the work of Gottschalk and Moffitt (1994). Although most scholars agree that earnings instability has increased over time, little is known about the causes of its increase.¹

An increase in workers' mobility across jobs (voluntary and involuntary) can potentially lead to transitory fluctuations in earnings if workers either experience an intervening spell of unemployment or experience a change in wages when changing jobs. So far the link between workers' mobility and earnings instability has received scant attention in the vast literature on earnings dynamics probably because identifying a clear decline in job security and job stability has proved elusive: A considerable amount of research has studied the frequency of job changes but most studies found very little, if any, increase over time - at least until the late 1990s (see among others Jaeger and Huff-Stevens 1999; Neumark et al. 1999; Farber 2008; Davis et al. 2012). However, even if the frequency of job changes has not increased much, earnings instability as a consequence of job change may have increased if job changers experience higher wage losses/gains upon job change.

There are various pieces of evidence both at the individual and at the firm level which are suggestive that higher earnings instability may be associated with a higher variance of earnings changes. Using PSID data, Kambourov and Manovskii (2008, 2009) show that there is a substantial increase in workers' mobility across occupation; Poletaev and Robinson (2008) show that wage losses of displaced workers are larger the larger the distance of the 'portfolio' of skills of their occupations before and after job loss. There is also evidence of an increase in the variance of growth rates of sales, employment and wages at the firm level (Comin and Philippon 2006; Comin et al. 2009) and that productivity dispersion across plants is positively correlated with individual wage inequality (Dunne et al. 2004; Leonardi 2007; Barth et al. 2014).²

¹See Gottschalk and Moffitt (2009) and Meghir and Pistaferri (2011) for complete overviews of the literature. Recently Guvenen et al. (2014) claim that the evidence of increasing instability is weaker in administrative data.

²Between-firm wage inequality also holds for the distribution of wages in other countries: Card et al. (2013) find that much of the increase in wage inequality in Germany is explained by increasing inequality across firms; Christensen et al. (2005) show that the cross-firm variance in (log) wages accounts for 60% of the total wage variance in Danish data.

The contribution of the present paper is twofold. In the first part of the paper, I assess the contribution of job changers to the evolution of the variance of earnings estimating an error component model. In addition to the traditional permanent and transitory components of wages, this model includes a match component (i.e. a shock to the worker-firm match whose variance is identified by job changers), to capture the idea that more inequality may result from workers changing jobs in an economy where firms become more unequal. I present complementary evidence from both PSID and SIPP data. The PSID is a necessary choice because is the only dataset that goes back for a sufficient period of time, however it is not the best dataset for looking at job changes because it averages earnings over different jobs. Therefore I complement the analysis using various waves of SIPP data, which cover a much shorter period of time but they record accurately job changes and the wage change between jobs. I find that the share of the variance of the match component in the total variance of earnings increases in both datasets, suggesting that job changers have an important role in explaining the evolution of instability over time.

The empirical results suggest the need to study the dispersion of productivity shocks across firms that may produce the divergence of earnings at the firm/match level. In the second part of the paper, I solve and calibrate an on-the-job search model with a mean-preserving spread of the distribution of productivity shocks which replicates the concurrent evidence of rising earnings instability and approximately constant job turnover. The model is based on the idea that there is a growing dispersion of productivities across firms and that job changers experience more instability in earnings because they match to an increasingly dispersed distribution of firms. The mean-preserving spread of the distribution of productivity shocks (shocks to the worker-firm match) induces more workers to search for better jobs and implies a larger increase in earnings instability for job changers than for job stayers. A stable job turnover is obtained when, in addition to an increase in the variance, there is also an increase in the mean of the distribution of productivity shocks (i.e. a non mean-preserving spread). In this case wages are higher, firms post less vacancies, and job turnover remains constant because not every search produces a new job match.

The last section of the paper provides a calibration of the model with plausible values of its parameters. The connection between the empirical part and the calibration section of the

paper is given by the estimates of the variance of the match component of wages, which I use to calibrate the parameter that governs the mean-preserving spread of the distribution of productivity shocks in the search model.

This paper is related to a number of branches of the literature. The empirical part of this paper is connected to a subset of the very large literature on earnings instability (both reduced form and structural) which has looked at the effects of job change. Some papers have looked at the effect of tenure on the permanent (Parent 2002) and transitory component of earnings (Cappellari and Leonardi 2015; Hospido 2012). Some other recent papers have focused on instability measures which include zero earnings, i.e., workers remaining without a job (Ziliak et al. 2011; Dynan et al. 2012; Celik et al. 2012; Cappellari and Jenkins 2014). Unlike this literature, the present paper looks explicitly at the contribution of job-to-job changers (i.e. without an intervening unemployment spell). I focus on job-to-job changers because the explanation of the rise in instability is likely to go beyond unemployment spells for two reasons: firstly unemployment declined in the 1990s while instability of low-skilled workers continued to increase (Gottschalk and Moffitt 2009) and secondly instability increased also for workers who did not experience unemployment (Huff-Stevens 2001).

A more structural strand of the literature on earnings instability has analyzed the economic forces behind the variability of earnings, building models which study individuals' behavior under restrictive functional assumptions (Flabbi and Leonardi 2010; Altonji et al. 2013). Low et al. (2010) distinguish between shocks and responses to shocks explicitly modeling job mobility in a search and matching framework.³ I borrow the empirical specification of the model from this paper, however, I do not model job mobility and work under the assumption that the sorting behavior of job changers across firms has not changed over time: I focus on trends rather than on the cross-sectional difference between job changers and stayers.

The on-the-job search model in the theoretical part of this paper is an application of Pissarides (1994, 2000) model to the analysis of the earnings variance of job stayers and job changers. Typically most papers use wage posting models (as opposed to Nash bargaining models) to study the behavior of wages because those models yield closed form expressions for

³This strand of the literature is concerned about the sources of economic risk and the degree as to which individuals anticipate (or are insured against) the observed earnings changes. In the absence of this information, this literature models different types of uncertainty: one associated with employment risk (i.e. rates of arrival of job offers), the other with productivity risk (i.e. shocks to the firm-worker match).

the wage distribution (see among others Christensen et al. 2005). I show that it is possible to generate increasing inequality in an extension of a standard on-the-job search model with a Nash bargaining wage determination process. Hornstein et al. (2011) claim that the introduction of on-the-job search in a model with Nash bargaining is necessary to replicate the high residual wage dispersion in the US labor market. Unlike this literature, I focus on the increase of inequality: a mean-preserving spread of the distribution of productivity shocks increases on-the-job searches and wage changes upon a job change, giving job mobility an important role in explaining the increase in inequality. An additional account of the relation of this model with the existing literature will be given in Section 4 when discussing the model's assumptions.

The rest of the paper proceeds as follows. Section 2 presents the variance decomposition model, Section 3 presents the results for both the PSID and SIPP data. Section 4 presents a search and matching model adapted to the study of the earnings instability of job stayers and job changers. Section 5 conducts a calibration exercise and Section 6 summarizes some conclusions.

2 An Error Component Model

Past literature suggests that in US data (usually PSID data), permanent income is a martingale and transitory income is serially uncorrelated or a first order Moving Average process: see, for example, Meghir and Pistaferri (2004) and Blundell et al. (2008). Since I am interested in the role of job changers, I include in the model a match component of earnings:

$$\log w_{ijt} = r_{it} + e_{it} + a_{ijt} \tag{1}$$

where $r_{it} = r_{it-1} + z_{it}$ is a random walk and $z_{it} \sim N(0, \sigma_{zt}^2)$ denotes the permanent income shock which is normally, independently and identically distributed across individual i and year t . Here, $e_{it} \sim N(0, \sigma_{et}^2)$ is the transitory shock and might be thought to represent also measurement error (Meghir and Pistaferri 2004). The match component $a_{ijt} \sim N(0, \sigma_{at}^2)$ is assumed to be normal i.i.d. (i.e. each successive draw a_{ijt} is independent of the previous one) and constant over the life of the worker-firm relationship jt which implies that the firm does not respond to outside offers and that returns to job tenure are very small.⁴ However, if the

⁴This is a reasonable assumption because the effect of tenure on wages is generally agreed to be small: Altonji

worker switches employers between $t - 1$ and t , there will be some resulting wage growth, which is a sort of a mobility premium, denoted by $\phi_{it} = (a_{ijt} - a_{ij(t-1)}) \sim N(0, \sigma_{\phi}^2)$. The purpose of the empirical part of the paper is to establish the relative importance of σ_{ϕ}^2 (which is equal to twice the variance of the match shock σ_a^2) over time.

The index j may wrongly suggest an employer identifier in the employer-employee matched data. Unfortunately, matched data in the U.S. are not public use data. In the absence of matched data one cannot distinguish between firm and match effects, and so a_{ijt} denotes a constant match-specific component –additional to individual productivity– in which $j(t - 1)$ indicates the firm that the worker joined in period $t - 1$ and jt the firm joined in t . Since the subscript j indicates that a_{ijt} refers to a match component (as opposed to an individual component), but may be confusing as a subscript of wages, it will be dropped from wages from now on.

This model is used in Low et al. (2010) in their structural model of job mobility as a response to employment and productivity shocks. While their paper is focused on modeling job mobility decisions in a cross-sectional dimension, selection issues of workers into jobs are not central in my argument as long as the sorting behavior of workers across firms is invariant over time.

Match shocks are identified by job changers, in fact, the model in one-year differences is:

$$\Delta \log w_{it} = r_{it} - r_{it-1} + e_{it} - e_{it-1} + I(M_{it} = 1)(a_{ijt} - a_{ijt-1}) \quad (2)$$

where M_{it} is an indicator for whether the worker changed firms in year t . The model is estimated in first differences because the focus of the paper is on the effect of job changes on earnings instability, in the Estimation Appendix I discuss briefly the comparison with models estimated in levels.

As is common in this strand of the literature, the model is estimated by Minimum Distance and the variances of the wage shocks are identified by restrictions imposed on the moments of wage growth:

and Williams (2005) place the consensus tenure effect at between 6.6% and 11% per decade. Postel-Vinay and Robin (2002) and Cahuc et al. (2006) present search and matching models where firms respond to outside offers that will be briefly discussed in Section 4. Notice that this specification of the match component as an i.i.d. shock implies a random matching process between workers and firms that will be modeled in Section 4.

$$\text{cov}(\Delta \log w_{it}, \Delta \log w_{it}) = \sigma_{zt}^2 + \sigma_{et}^2 + \sigma_{et-1}^2 + I(M_{it} = 1)\sigma_{\phi t}^2 \quad (3)$$

$$\text{cov}(\Delta \log w_{it}, \Delta \log w_{it-1}) = -\sigma_{et-1}^2 \quad (4)$$

Notice that the variance $\sigma_{\phi t}^2$ (which is equal to twice the variance of match shocks $\sigma_{at}^2 + \sigma_{at-1}^2$) is identified by job changers, i.e. is conditional on $M_{it} = 1$. As mentioned in the Introduction, I use both PSID and SIPP data because they are complementary: the PSID data are consistent over time and cover a long time span; the SIPP data consist of repeated waves (short panels) taken in various years but it is more accurate in defining a job change. In the PSID, there are no employer identifiers, but one can infer whether the worker has changed firms ($M_{it} = 1$) because of having less than 12 months of tenure (this will imply that we have to use two-year differences in PSID data as explained in the next section). In the SIPP, each firm an individual is working for is assigned an ID, and therefore $M_{it} = 1$ if the employer the individual is working for at time t is different from the one being worked for at time $t - 1$.

3 Evidence on the Variance of Wage Changes

I use PSID data on the real hourly earnings of all male heads of households aged 25 to 60 with valid information on tenure and at least two consecutive years of positive earnings between 1976 and 2007 (ever since 1997, the PSID data has been biannual). Details on the step by step sample selection are given in the Data Appendix; the final sample includes 8,119 individuals and 71,786 observations.

As mentioned above, I define job changers in year t as those individuals with strictly less than 12 months of tenure in year t .⁵ One possible concern is that the change in earnings consequent to a job change cannot be exactly measured, since the PSID records annual earnings, and earnings during the year of the job change are a mixture of the earnings from the old and the

⁵The variable of primary interest indicates the “time the worker has been with their current employer”. The tenure question switched from being coded in intervals prior to 1976 to being measured in months: for this reason I use data from 1976 onwards. Many of the difficulties related to measuring job tenure in the PSID are discussed in Jaeger and Huff-Stevens (1999). The question asks about employer tenure, and so in this paper job changers are those who change jobs between firms, i.e. they are actually employer changers. But in the first years of the survey, the question was about “time the worker has been in his current position”, and in some cases this has been mistaken for changes within the firm. This explains the higher number of changers in the early years.

TABLE 1. PSID Descriptive Statistics, By Year

Year	N	age	$\log w_{it}$	$\log w_{it+2} - \log w_{it}$	% job changers
1976	2057	37.95	2.78	0.06	0.12
1977	2201	37.91	2.78	0.02	0.13
1978	2494	37.79	2.78	-0.04	0.18
1979	2758	37.64	2.75	-0.02	0.18
1980	2852	37.39	2.72	0.03	0.17
1981	2851	37.31	2.70	0.06	0.13
1982	2832	37.35	2.74	0.04	0.12
1983	2792	37.26	2.74	0.05	0.11
1984	2824	37.18	2.74	0.08	0.13
1985	2950	37.14	2.75	0.05	0.13
1986	3019	37.27	2.76	0.03	0.13
1987	3065	37.40	2.75	0.04	0.14
1988	2661	37.04	2.78	0.01	0.12
1989	2640	37.31	2.77	0.02	0.12
1990	2673	37.48	2.75	0.06	0.11
1991	2655	37.77	2.75	0.09	0.10
1992	2638	37.95	2.77	0.05	0.09
1993	2625	38.32	2.83	0.00	0.07
1994	2768	38.79	2.80	0.01	0.08
1995	2905	39.13	2.79	0.02	0.09
1996	2867	39.54	2.78	–	0.08
1997	2331	39.73	2.78	0.07	0.08
1999	2385	40.32	2.82	0.08	0.09
2001	2472	40.85	2.87	-0.02	0.09
2003	2527	41.07	2.81	0.04	0.09
2005	2584	41.10	2.80	0.04	0.10
2007	2360	42.71	2.85	–	0.09

Notes: N=8,119; NT=71,786. Sample of male head of households aged 25 to 60. Hourly labor income is in year 2000 dollars. When taking two-year earnings differences the number of observations is 52,848. Individuals are job changers when they have less than 12 months of tenure in year t .

new job. For job changers in year t , the problematic income which mixes earnings in the two jobs is recorded in $t + 1$ (the PSID survey in $t + 1$ records the annual income of the previous year). To avoid this problem, I take two-year differences in log earnings: $(\log w_{it+2} - \log w_{it})$. Since from 1997 on the PSID data are biannual, I have overlapping two-year differences for 1976-1978 and 1977-1979 until 1995-1997 and non overlapping two-year differences from 1997-1999 on (Shin and Solon 2011; Dynan et al. 2012). Table 1 describes the characteristics of the final sample. Notice that, when taking two-year differences in earnings, the number of usable observations goes down from 71,786 to 52,848.

Following most of the literature, I estimate the first-stage residuals from the following fully-

interacted model:

$$\log w_{it+2} - \log w_{it} = X_{it}\beta + g_{it} \quad (5)$$

where the covariates are age, age squared, year dummies, and interactions. All of the analysis will be conducted on the residuals g_{it} .⁶

Figure 1 plots, as it changes over time, the cross-sectional variance in the log residuals of the two-year differences in earnings of the full sample of individuals, and the same for job stayers and job changers separately. The pattern of flat instability in the full sample after the 1980s is consistent with the findings of other papers in the literature that estimate error component models using earnings differences (Shin and Solon 2011; Dahl et al. 2011; Celik et al. 2012; Dynan et al. 2012).⁷ The picture shows that job changers experienced a much higher increase in instability, than did the job stayers, who had a stable variance. This suggests that they may have played an important role in the increase of earnings instability over time.

Figure 2 uses a specific question in the PSID survey to investigate whether there are differences between involuntary and voluntary job changers, and plots the variances separately for the sample of those who were laid off and the sample of those who quit.⁸ Except for the late 1970s, there does not seem to be a big difference between the evolution of the variance of the quitters' log hourly earnings changes and that of those laid off. From now on, I do not distinguish between these two groups, since both the quitters and those laid off have seen a similar pattern of instability over time.

⁶An alternative is to run three different regressions, one for each education group (college, high school, less than high school) to allow for time-varying education premia. This does not change the results. Nor the results are changed if wage changes are purged using a set of interactions of year dummies with two-digit industry and two-digit occupation dummies (industry and occupation are recoded using the Retrospective Files as in Kambourov and Manovskii 2008).

⁷This pattern of results does not depend on panel attrition because it does not change substantially if I use the 'balanced' sample of individuals who have valid information on tenure and earnings for nine or more years. The evolution of estimated instability is slightly different in models of earnings specified in levels (rather than differences) which find increases of instability also during the 1990s. The explanation of the different results lies in the fact that the variance of short-term changes in earnings is composed of two separate components which have offset each other over time: On the one hand, the rising variance of transitory shocks increases the variance of changes in earnings; on the other hand, the rising persistence of those autocorrelated shocks reduces changes in earnings (Moffitt and Gottschalk 2012).

⁸The type of change is determined by the answer to the question: "What happened to the job you had before—did the company go out of business, were you laid off, promoted, or what?". The four reasons identified in the survey are (1) quit, (2) permanently laid-off or fired, (3) business or plant closed, (4) other reason (mainly seasonal or temporary job ended). I define voluntary changers as those who responded (1). The information on the type of change is present for 85% of job changes (55% of those are quits) and is missing after 2001.



FIGURE 1. The variance of log residual two-year changes in earnings for the full sample and separately for job stayers and job changers.

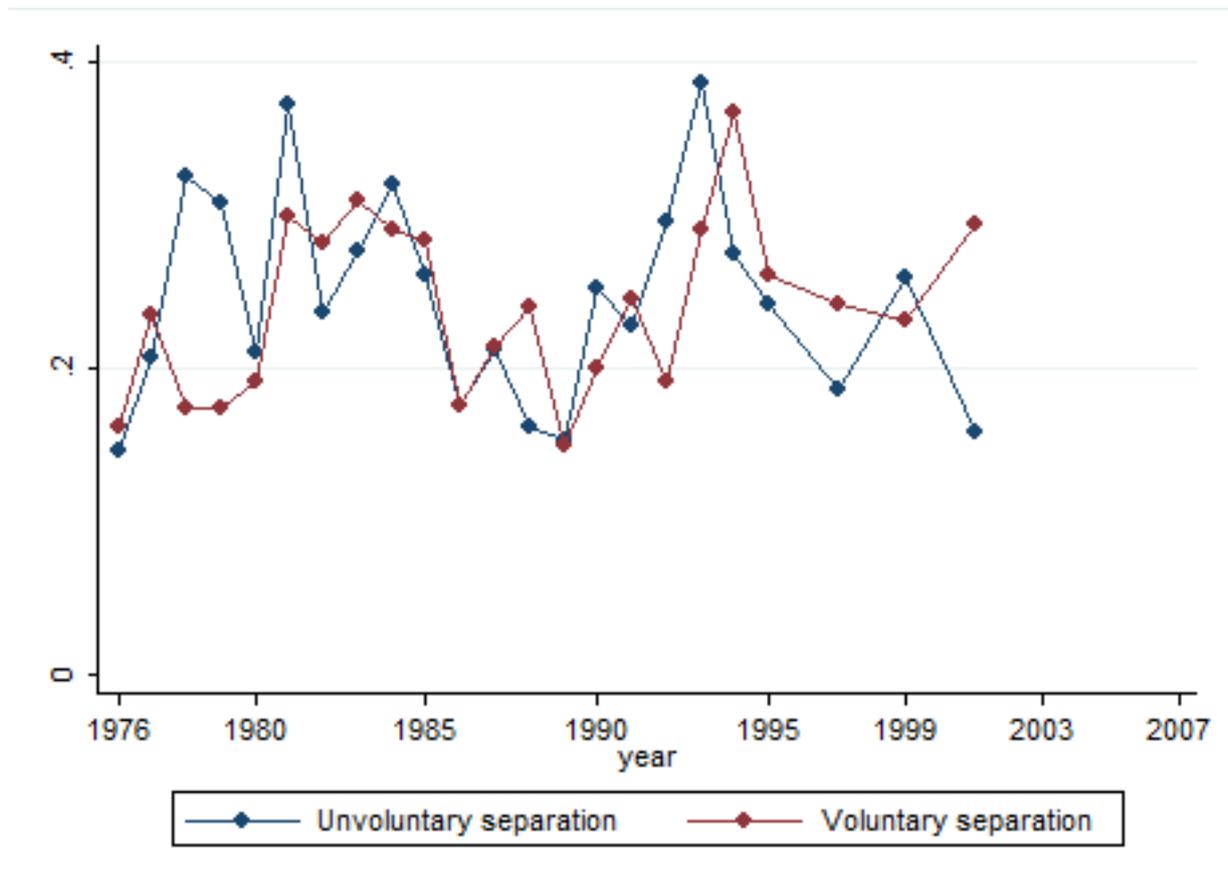


FIGURE 2. The variance of log residual earnings changes of voluntary and involuntary job changers.

3.1 Model Estimation with PSID Data

To decompose the cross-sectional variance of earnings changes into its different components, I adapt the error component model of Section 2 to the two-year earnings changes determined from the PSID data, and use it to estimate the relative importance of the match shocks over time (see the Estimation Appendix for details). In this formal model the role of job changers is embodied in the variance of the mobility component of earnings $\sigma_{\phi}^2 = 2\sigma_a^2$.

Table 2 shows the estimates of the variances of the earnings components in each year and the standard errors. Notice that, while the simple measure of the variance of two-year earnings changes needs only two years of data observations (e.g. in Figure 1), the decomposition with the formal model needs three years of data because it makes use of the first order auto-covariance. Therefore the first year of the variance decomposition is 1978 (as opposed to 1976).

All estimates are very significant except for two variances of the permanent shocks (in year 1993 and 2003) which are estimated to be very small and are insignificantly different from zero. On average (taken over the whole sample), the variance of the permanent shock, σ_z^2 , is equal

TABLE 2. Error Component Model: Wage Variance Estimates.

Year	Permanent shock σ_z^2		Match shock σ_a^2		Transitory shock σ_e^2	
	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.
1976	–	–	–	–	–	–
1977	–	–	–	–	–	–
1978	0.03451	0.00912	0.03839	0.00903	0.02759	0.00828
1979	0.03172	0.00888	0.03759	0.00885	0.03474	0.00807
1980	0.02698	0.00847	0.03532	0.00912	0.03411	0.00765
1981	0.01365	0.00833	0.10827	0.01066	0.04095	0.00751
1982	0.02251	0.00828	0.07061	0.01129	0.03656	0.00746
1983	0.01879	0.00823	0.08591	0.01115	0.04225	0.00743
1984	0.01031	0.00826	0.08935	0.01031	0.04756	0.00745
1985	0.01657	0.00815	0.08139	0.01017	0.04543	0.00738
1986	0.00718	0.00867	0.04877	0.01079	0.03583	0.00784
1987	0.01523	0.00859	0.06308	0.01056	0.02653	0.00775
1988	0.01182	0.00855	0.08201	0.01128	0.02573	0.00772
1989	0.00798	0.00859	0.04130	0.01164	0.02917	0.00775
1990	0.02010	0.00860	0.06269	0.01191	0.02380	0.00777
1991	0.04019	0.00871	0.05828	0.01239	0.02198	0.00788
1992	0.02438	0.00875	0.05345	0.01373	0.03517	0.00792
1993	-0.00392	0.00867	0.09638	0.01468	0.06851	0.00787
1994	0.00171	0.00864	0.11818	0.01300	0.05524	0.00789
1995	0.01839	0.00977	0.07625	0.01461	0.03897	0.00892
1996	–	–	–	–	–	–
1997	0.01725	0.00908	0.04797	0.01378	0.04267	0.00828
1999	0.01198	0.00861	0.06350	0.01230	0.04573	0.00776
2001	0.03077	0.00861	0.05356	0.01266	0.04592	0.00778
2003	-0.00492	0.00859	0.09972	0.01259	0.08699	0.00778
2005	0.00765	0.00846	0.06053	0.01151	0.05454	0.00765
2007	–	–	–	–	–	–

Notes: The model is estimated on 88,094 earnings moments of 7,114 individuals over the period 1978–2005 from PSID data.

to 0.016 while the variance of the match shock, σ_a^2 , is equal to 0.065. This means that match heterogeneity is an important component of wage dispersion: on average, wages for the same individual drawing different match components could vary by as much as ± 51 percent (i.e. \pm two standard deviations) with a probability of 95 percent. The variance of the permanent shock is, correctly, small, because the shocks are permanent and because of the presence of the match component in the model's specification (Low et al. 2010). Table 2 also shows that the estimates of the variances of the transitory shocks are large and increasing over time but the transitory shock here is modeled as a white noise and has no clear economic interpretation.

The most notable finding shown in the table is that the estimated variance of the mobility shocks increases over time. Figure 3 plots the estimated variances of the permanent and of the match shocks year by year (the shaded areas indicate the standard errors of the estimates). The figure shows an increasing variance of the match shocks and a rather flat profile of the variance of the permanent shocks which suggests that the increasing pattern of the variance of wage changes originates from shocks to the match component of the wage rather than from shocks to permanent individual characteristics. Using the information on the share of job changers and the theoretical covariance structure of the model (see Equation 4 and the Estimation Appendix) one can easily calculate the contribution of the *increase* in the variance of match shocks $((2\sigma_{a2005}^2 - 2\sigma_{a1978}^2)M_{i1978})$ to the *increase* in the total variance of wage changes.⁹ The estimated variance of the match shocks increased by 0.014 points $(=(0.156-0.076)*0.18)$ between 1978–1979 and 2003–2005, and concurrently the total variance of log earnings changes increased by 0.062 points $(=0.158-0.096)$. Therefore the increase in the variance of the match shocks can explain around 23% $(=0.014/0.062)$ of the total increase in the variance of wage changes.

3.2 Model Estimation with SIPP Data

As mentioned above, one of the main limitations of the PSID data is that it mixes the earnings of different jobs in the year of the job change. An important advantage of the SIPP over the PSID is that the SIPP does not average the pay over different employers: it records all job-to-job transitions and the resulting new wage each time. Thus the full effect of a move from

⁹Notice that the share of job changers is kept constant at its 1978 level (18%) to isolate the effect of the change in the estimated variance of the mobility component from the change in the share of job changers. To smooth the point estimates in year 1978 and 2005, I take the mean of the estimates over the first two years of the sample 1978–1979 and the last two years 2003–2005.

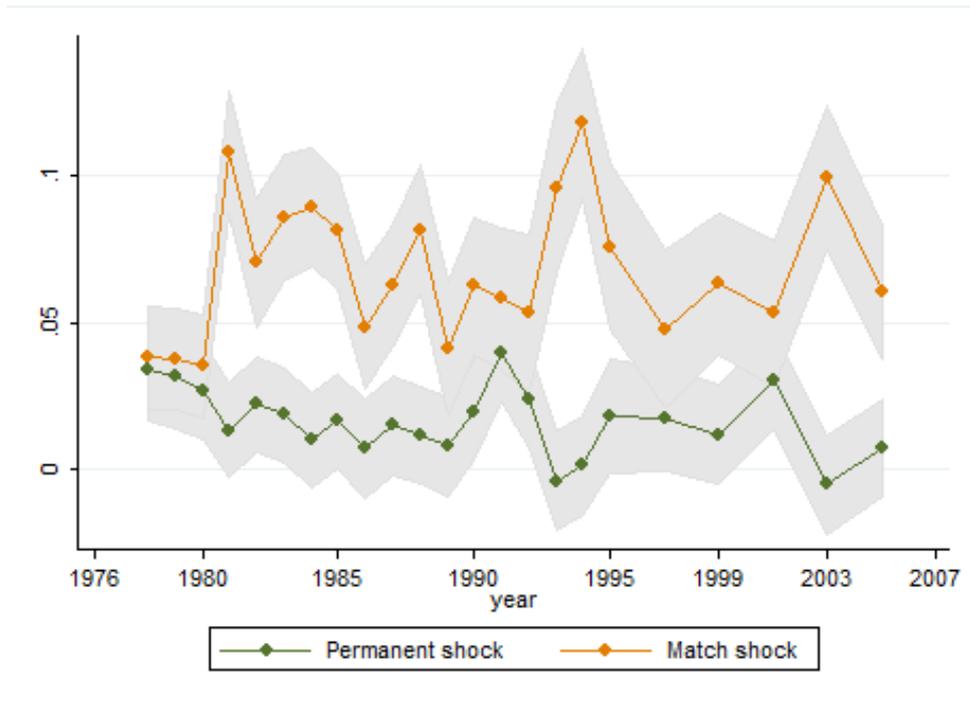


FIGURE 3. Estimated variances of permanent and match shocks. Shaded areas indicate standard errors.

one employer to another is observed. This allows me to estimate the error component model of Equation 2 in year-to-year differences rather than in two-year differences as I did above with the PSID.

I use the 1993, 1996, 2001, 2004 and 2008 panels of the Survey of Income and Program Participation (SIPP) and estimate the variance components separately on each panel.¹⁰ I select males aged 25 to 60 and I build a consistent sample in each panel to be able to compare the estimates of the variance components obtained in different periods of time (and with the PSID results). Each column of Table 3 shows the descriptive statistics of the sample for each of the five panels. The details of the sample selection criteria, which are common to all panels, are in the Appendix.

As I did with PSID data, I use the residuals from the following regression, run separately on each SIPP panel: $\Delta \log w_{it} = X_{it}\beta + g_{it}$, where X_{it} includes age, age square, a dummy for marital status, a dummy for being a non-profit firm, and four industry dummies.

Table 4 shows the estimated variances of the three error components (indicated as σ^2): each column of the table corresponds to a SIPP panel. The estimated variances of the match

¹⁰Each SIPP panel contains at least three years of data –for example the 1993 panel contains data also on 1994 and 1995– so that it is possible to estimate the error component model separately on each panel. The 1996 redesign introduced some changes such as a single 4-year panel instead of overlapping monthly panels and computer assisted interviews.

TABLE 3. SIPP Descriptive Statistics

Panel	1993	1996	2001	2004	2008
Hourly wage (dollar price=2010)	22.036 (13.937)	22.190 (20.387)	24.495 (19.775)	25.185 (23.262)	25.198 (21.149)
% job changers	0.100	0.199	0.141	0.124	0.134
Age	39.397 (9.573)	35.075 (8.996)	40.854 (9.533)	42.074 (9.461)	42.426 (9.980)
White	0.893	0.893	0.865	0.846	0.839
Married	0.731	0.692	0.702	0.723	0.697
Completed high school	0.578	0.678	0.602	0.676	0.696
Agriculture and construction	0.104	0.136	0.118	0.138	0.134
Manufacturing	0.542	0.545	0.507	0.357	0.318
Services	0.264	0.248	0.290	0.405	0.453
Public services	0.090	0.072	0.086	0.100	0.095
Not for profit firm	0.035	0.040	0.048	0.047	0.048
No. observations	21,482	13,274	14,966	16,765	28,168
Wage changes					
$\Delta \log w_{ijt}$	0.029 (0.236)	0.019 (0.352)	0.012 (0.356)	0.021 (0.272)	0.009 (0.276)
% positive changes	[0.532]	[0.551]	[0.508]	[0.528]	[0.510]
No. observations	15,465	9,979	10,686	12,934	20,352
Within-job $\Delta \log w_{ijt}$	0.028 (0.210)	0.014 (0.293)	0.006 (0.322)	0.021 (0.220)	0.011 (0.214)
% positive changes	[0.530]	[0.548]	[0.503]	[0.525]	[0.510]
No. observations	13,925	7,987	9,185	11,329	17,637
Between-job $\Delta \log w_{ijt}$	0.045 (0.402)	0.039 (0.526)	0.050 (0.516)	0.021 (0.504)	-0.003 (0.525)
% positive changes	[0.558]	[0.564]	[0.538]	[0.544]	[0.515]
No. observations	1,540	1,992	1,501	1,605	2,715

Notes: Each column refers to a specific SIPP panel. Sample of males aged between 25 and 60 who are not self-employed, the sample selection criteria are common to all panels (see Appendix for more details). Standard deviations of non-binary variables in parentheses.

TABLE 4. Error Component Model: SIPP Results

Wage variance estimates					
Panel	1993	1996	2001	2004	2008
σ_a^2 match shock	0.063 (0.004) [29%]	0.083 (0.007) [25%]	0.076 (0.007) [16%]	0.100 (0.008) [30%]	0.110 (0.009) [37%]
σ_z^2 permanent shock	0.016 (0.002) [36%]	0.058 (0.012) [43%]	0.043 (0.005) [33%]	0.034 (0.004) [43%]	0.023 (0.002) [29%]
σ_e^2 transitory shock	0.008 (0.001) [35%]	0.022 (0.003) [32%]	0.033 (0.003) [51%]	0.010 (0.002) [26%]	0.014 (0.001) [34%]

Notes: Each column refers to a specific SIPP panel. Variances of shocks are estimated on residual log hourly earnings changes separately in each SIPP panel. Standard errors in parentheses and share of total variance in square parentheses. The share of the total variance is calculated with the formula $E(g_{it}, g_{it}) = \sigma_z^2 + 2\sigma_e^2 + 2\sigma_a^2 M_{it}$, where g_{it} indicates the residual hourly earnings change and M_{it} is the share of job changers in each SIPP panel.

shocks are always larger than those for the permanent shocks, as with the results obtained from the PSID data. The estimated variances of the transitory shocks are instead lower than those obtained from the PSID data, probably reflecting the much better identification of job changers in the SIPP than in the PSID, something which would reduce the extent of the measurement error. Table 4 shows that there is a rising trend in the variance of match shocks: the estimates range from 0.063 in the 1993 panel to 0.110 in the 2008 panel. Using Equation 4, there can be attributed to each component of the variance a share of the total variance of the wage changes (in square parentheses in Table 4). The share of the variance of the match component in the total variance increases from 29% in 1993 to 37% in 2008. To isolate the contribution of the increase in the variance of the match shocks to the increase in the total variance, I keep the share of job changers fixed at its initial value in 1993 (i.e. 10%). Since the increase in the total variance of residual log wage changes between 1993 and 2008 has been 0.035 log points ($=0.079-0.044$), the increase in the estimated variance of match shocks ($((2\sigma_{a2008}^2 - 2\sigma_{a1993}^2)M_{i1993})$) explains around 26% ($=(0.221-0.127)*0.1/0.035$) of the increase in the total variance.

In conclusion, the increase in the variance of match shocks explains a substantial share of the total increase in the variance of wage changes both in PSID and in SIPP data (varying between 23% and 26%). These results are consistent with evidence reported from other sources: for

example, Comin and Philippon (2006) using Compustat data report an increase in the variance of firm-level mean wages of 10% to 20% depending on the measures used; Barth et al. (2014) decompose the change in wage variance from 1992 to 2007 in employer-employee matched data and show that the variance of mean wages between-establishment dominates changes over time. While none of these papers focusses on the role of job changers, the implication of the findings shown above is that much of the increase in the variance of earnings differences is explained by job changers rather than job stayers.¹¹

The variance decomposition exercise highlights the importance of match shocks and of job changers but does not help explain it. However the empirical results are suggestive of diverging wage levels at the firm/match level and of the need of studying the role of productivity shocks (for example associated with the introduction of innovative products) in producing the divergence of firm-level earnings. In an attempt to interpret these results, the next section will provide a model of on-the-job search where the source of shocks lies in productivity shocks on the demand side. By converse, as I did in the estimation of the error component model, I will continue to ignore job mobility issues on the supply side, i.e., I present a random matching model where workers are matched randomly to firms. The model highlights the role of job-to-job change (rather than job change linked to unemployment) and the role of the variance of wage changes for job changers rather than the increase in job turnover (because most evidence points to a stable level of job turnover, at least until recently, as discussed in the Introduction).

4 The Model

This section solves an extension of a simple on-the-job search model with the standard Nash bargaining wage determination process (Pissarides 1994, 2000) which generates increasing wage inequality of job changers. The results are obtained through a mean-preserving spread of the distribution of productivity shocks (shocks to the productivity of the firm-worker match), which may be thought to reflect the increasing uncertainty of demand.¹² At the end of the next section,

¹¹I have included in the SIPP sample only those individuals with positive earnings in each month of the sample (see the Appendix for the details) therefore they are likely to be voluntary changers who may have had, if any, only very short periods of unemployment between two different jobs. The focus on job changers in both the PSID and SIPP data has neglected the potential role of unemployment. However, as we mentioned in the introduction, unemployment alone can hardly explain the evolution of earnings instability over time.

¹²For example, Comin and Philippon (2006) attribute higher firm volatility to higher competition in the goods market. They find that firm volatility increased after deregulation and that the increase in firm-level volatility

I will also calibrate a non mean-preserving spread of the distribution of productivity shocks to improve the fit of the model with respect to the evidence on job turnover.

In this model, ex ante identical workers are matched randomly to firms whose distribution of productivity becomes more dispersed over time (firms and matches coincide in this model). Productivity shocks in the model correspond to match shocks in the empirical part (and to mobility shocks for job changers). The main element of interest is the wage variance of job changers and job stayers as predicted by the model before and after the mean-preserving spread of match productivities.¹³

The hypotheses of the model are the following:

(i) Workers are ex ante identical, with permanent productivity p normalized to 1, i.e. the model abstracts from individual permanent characteristics and focuses on the role of match shocks to the earnings distribution.

(ii) Job seekers (employed and unemployed) and jobs are matched via a matching function $m = m(v, u + e)$, where u indicates the unemployed job seekers, e the employed job seekers, and v the number of vacancies. Jobs arrive at each searching worker, employed or unemployed, at the rate $\theta q(\theta)$, where $q(\theta) = m(1, \frac{u+e}{v})$ and $\theta = \frac{v}{u+e}$ is the ratio of vacancies to job seekers.¹⁴

(iii) The match has idiosyncratic productivity x . Every new match is created at maximum productivity px with $x = 1$. After being created, the match is hit by an idiosyncratic productivity shock $x \rightsquigarrow G(x)$ with $x \in [0, 1]$ at Poisson rate λ . The shock is transitory: every x' is independent of the previous x .

With these hypotheses the model can be characterized by two reservation rules. There is a reservation productivity R such that jobs $x < R$ are destroyed and workers end in unemployment. There is a second reservation productivity S such that workers in jobs $R \leq x \leq S$ seek a new job in the hope of finding a new match at the maximum productivity (equal to one).

Workers in jobs $S < x \leq 1$ do not search, because search is costly and they are satisfied with

is correlated with high research and development (R&D) activity as well as more access to the debt and equity markets.

¹³The comparative statics exercise with the general equilibrium solution of the model is based on the assumption of stationarity of the model. This implies that we are looking at two different points in time and we find them generating different parameters. In the context of the data, this means assuming that the observations at the beginning and at the end of the period (in the PSID data, this means 1976 and 2007; in the SIPP data, 1993 and 2008) belong to two different steady states, even if we do not know exactly when the mean-preserving spread took place between the two periods before and after the change.

¹⁴By the usual properties of the matching function $q'(\theta) < 0$ and the elasticity of $q(\theta)$ is in absolute value $0 \leq \eta(\theta) \leq 1$.

their high-productivity match.

These hypotheses are standard in on-the-job search models but deserve to be discussed. The crucial assumption is that a worker receives a shock which induces starting searching for a new job, renegotiating the wage (as we will see below, he will have to compensate the firm for the likely possibility that he will eventually quit), and when he eventually finds a new match, moving to the new job with productivity equal to one. Job changers move from a job with productivity x to a job with productivity $x = 1$, therefore an increase in the variance of x correspond to a mobility shock of the previous empirical section. The assumption that $x = 1$ in all new jobs is admittedly unattractive but has the advantage of keeping the model tractable even when solving it with a mean-preserving spread of the distribution of shocks. A consequence of this assumption is that the distribution of wages in new hires (new hires both from the pool of the employed job seekers or from the unemployed) is degenerate. However, the wage distribution of the employed job seekers before the job change will be affected by the mean-preserving spread, and so will the distribution of the wage changes between the two jobs.

Other models of on-the-job search (for example, Burgess and Turon 2010) relax this assumption and propose a more realistic vacancy creation process, with heterogeneous vacancies created over a range of idiosyncratic productivities. This complication is justified by their focus on showing that it is possible to generate volatility in unemployment and vacancies to match the actual data. In my paper, the focus is on the shock to the match x and on the role of job changers in determining wage inequality. Therefore I do not need heterogeneity in vacancies but rather in the range of shocks that give rise to searches. I keep the model simple in order to be able to find a closed-form solution and to study the comparative statics relative to the parameter that governs the variance of the distribution of shocks.

The second important assumption is that of the existence of a fixed search cost and of a threshold S that distinguishes on-the-job seekers from non-seekers. A different specification would posit that all workers are searchers with an intensity decreasing in the value of the match (see for example Hertweck 2010). This would imply a higher search intensity in consequence of a mean-preserving spread of the distribution of shocks, but would not increase the number of job seekers: therefore the effect of the spread on wages would be driven only by its effect on the matching probability rather than on the distinction between changers and stayers, which

is the crucial message of this paper.

Lastly, other models of on-the-job search (for example, Postel-Vinay and Robin 2002 and Cahuc et al. 2006) model the decision to quit in a more realistic way by letting the worker compare wage offers and letting the firm make counter offers in an attempt to retain the worker. However these papers do not explicitly model the decision to search on-the-job, as they assume the cost of this search to be zero.

4.1 Workers

The expected returns of the employed worker when searching on the job W^s and when not searching W^{ns} are, respectively:

$$rW^s(x) = w^s(x) - \sigma + \lambda \int_R^1 \max(W^{ns}(s), W^s(s))dG(s) + \lambda G(R)U - \lambda W^s(x) + \theta q(\theta)[W^{ns}(1) - W^s(x)] \quad (6)$$

$$rW^{ns}(x) = w^{ns}(x) + \lambda \int_R^1 \max(W^{ns}(s), W^s(s))dG(s) + \lambda G(R)U - \lambda W^{ns}(x) \quad (7)$$

where r is the discount factor and $w^s(x)$ and $w^{ns}(x)$ denote, respectively, the wages of seekers and non-seekers. When $x < R$, jobs are destroyed and workers get the value of unemployment U . The difference between $W^s(x)$ and $W^{ns}(x)$ is the cost of search σ and the capital gain the job seeker enjoys when changing jobs, $\theta q(\theta)[W^{ns}(1) - W^s(x)]$, where $\theta q(\theta)$ is the rate at which job seekers find a new match and $W^{ns}(1)$ is the value of the new job (jobs are always created at maximum productivity $x = 1$).

The flow value of unemployment is:

$$rU = z + \theta q(\theta)[W^{ns}(1) - U] \quad (8)$$

where z is the unemployment benefit.

4.2 Firms

The value of a filled job depends on whether the worker is searching or not:

$$rJ^s(x) = x - w^s(x) + \lambda \int_R \max(J^{ns}(s), J^s(s))dG(s) - [\lambda + \theta q(\theta)][J^s(x) - V] \quad (9)$$

$$rJ^{ns}(x) = x - w^{ns}(x) + \lambda \int_R \max(J^{ns}(s), J^s(s))dG(s) - \lambda[J^{ns}(x) - V] \quad (10)$$

When the worker is searching, $J^s(x)$ contains an additional probability that the job is destroyed, given by the probability that the job seeker finds a new match $\theta q(\theta)$. The flow value of a vacancy is:

$$rV = -c + q(\theta)[J^{ns}(1) - V] \quad (11)$$

where c is the flow cost of a vacancy. The zero-profit or free entry condition is $V = 0$.

4.3 Wages

In this economy, wages $w(x)$ depend on the transitory match shock x because they are renegotiated after each match shock x .¹⁵

Wages are set by the Nash rule to share the surplus of a match. Because wage negotiation occurs once the worker is on the job and has no option of going back to the job that has just been left, I assume that the worker's outside option is always unemployment. Pissarides (1994) and Burgess and Turon (2010) make the same assumption, based on the impossibility of returning to the old employer for a worker who has quit that job, and on the impossibility of committing to a long-term contract so as to attract an employed worker for the prospective firm. Besides, it is never optimal for a firm to attempt to retain a worker with an outside offer by making a counter-offer, therefore the potential outside offer never becomes a new outside option for the worker in the wage bargaining process as it would in Postel-Vinay and Robin (2002) and in Cahuc et al. (2006).

¹⁵Wages in the model depend only on the realizations of the i.i.d shocks x . However, the shock x arrives at the Poisson rate $\lambda < \infty$, i.e. there are periods without shocks. Similarly to the empirical specification, match shocks to wages need a certain degree of persistence. In fact, if wages were continuously reset, nobody would search.

Therefore, for job seekers and non-seekers $i = s, ns$:

$$W^i(x) - U = \frac{\beta}{1 - \beta} J^i(x) \quad (12)$$

Substituting the value of a filled job for employed workers and for firms in the Nash rule, we find the wage equations for seekers (indicated by the superscript s) and non-seekers (superscript ns):

$$w^s(x) = (1 - \beta)(z + \sigma) + \beta x \quad \text{for } x \in [R, S] \quad (13)$$

$$w^{ns}(x) = (1 - \beta)z + \beta(x + c\theta) \quad \text{for } x \in (S, 1] \quad (14)$$

where β, z, σ and c are, respectively, the bargaining power of the workers, the unemployment benefit, the search cost for on-the-job seekers and the flow cost of a vacancy. As usual in the Nash bargaining framework, firms and workers share the surplus of a job (hence the term βx in both $w^s(x)$ and $w^{ns}(x)$). Seekers sustain the search cost σ , for which they are partially compensated (hence the term σ in $w^s(x)$). Since there is an assumption of perfect information, non-seekers must be paid more than seekers because seekers have to compensate the firm for the likely possibility of quitting (hence the term $c\theta$ in $w^{ns}(x)$).

In this framework, an endogenous fraction of workers, employed by lower productivity firms, will opt to search on-the-job. This is efficient and increases the value of the worker–firm match. The worker shares some of the expected benefit of the search with the firm by agreeing to a lower wage in the Nash bargaining. In jobs with low idiosyncratic productivity, there are expected benefits for the worker of a job search, as the expected value of a future job (which is equal to one) is high enough compared to the value of the current job to more than offset the search cost. For the firm, employed job search represents a cost, as it has to expect to have to open a new vacancy in the near future, and the value of a vacant job is always lower than the value of the filled job. These two facts imply that the wage rate for workers engaged in on-the-job search is lower than the wage rate they would get if they were not searching.

4.4 Equilibrium

An equilibrium in this model is a value of the thresholds S , R , market tightness θ , wage $w(x)$ and unemployment u . I solve the model assuming a uniform distribution $G(x)$ over the range $[0,1]$ and a parametric mean-preserving spread of the productivity distribution: $x(h) = x + h(x - \bar{x})$ where \bar{x} is the mean of the distribution and $h \geq 0$ is a parameter. I shall consider the effect of a marginal shift dh on the steady-state equilibrium, evaluated in the neighborhood of the old equilibrium, $h = 0$. In order to make the analysis more meaningful, I will assume that $\bar{x} > rU$, i.e., that the reservation wage of the unemployed job seekers is below mean productivity so that the multiplicative shock dh reduces the productivity of at least some active low-productivity jobs (Pissarides 2000). The assumption of the uniform distribution (without loss of generality) is common in models of on-the-job search with the two thresholds S and R because it allows reading the comparative statics of the model on the number of job seekers ($S - R$) (Burgess and Turon 2010).

Changes in the number of employed job seekers come from productivity shocks in and out of the range $[R, S]$. The evolution of the number of employed job seekers e is given by:

$$\frac{de}{dt} = \lambda(1 - u)(S - R) - \lambda e - \theta q(\theta)e. \quad (15)$$

In each period λ , job seekers receive a shock and leave the stock of job seekers. Those who newly enter (or re-enter) the pool of job seekers are only those who receive a shock in the range $[R, S]$. The number of job changers is given by $\theta q(\theta)e$: they leave the stock of job seekers because they find new jobs. From Equation 15, the fraction of employed job seekers in steady state is given by:

$$\frac{e}{(1 - u)} = \frac{\lambda(S - R)}{\lambda + \theta q(\theta)} \quad (16)$$

and the job-to-job turnover rate is the fraction of job seekers who find a match, i.e. $\frac{\theta q(\theta)e}{1 - u}$. The steady state level of unemployment is $u = \frac{\lambda R}{\lambda R + \theta q(\theta)}$.

The reservation rule S is such that the value of a job x , when the worker is searching on the job, is equal to the value when not searching: $W^{ns}(S) = W^s(S)$. The job creation condition is given by $J^{ns}(1)$ and the zero profit condition $V = 0$. The job destruction condition is determined by a job reservation productivity R such that $J^s(R) = 0$. The equation that

determines S , the job creation condition, and the job destruction condition, take, respectively, the following forms:

$$\frac{(1+h)(S-R)}{r+\lambda+\theta q(\theta)} = \frac{\beta}{1-\beta} \frac{c}{q(\theta)} - \frac{\sigma}{\theta q(\theta)} \quad (17)$$

$$\frac{(1+h)(1-R)(1-\beta)}{r+\lambda} = \frac{c}{q(\theta)} + \frac{\beta c \theta - (1-\beta)\sigma}{(r+\lambda)} \quad (18)$$

$$(1+h)R - h\bar{x} + \Lambda(R, \theta, \sigma, h) = z + \sigma \quad (19)$$

where $\Lambda(R, \theta, \sigma, h) = \lambda \int_R^1 \max(J^{ns}(s), J^s(s)) dG(s)$ is the option value of the job with $\frac{d\Lambda}{d\theta} < 0$, $\frac{d\Lambda}{dR} < 0$ and $\frac{d\Lambda}{dh} > 0$ (all these results are derived in the Appendix).

The job creation (henceforth JC) curve 18 is negatively sloped in the space R, θ and implies that the expected productivity gain from job creation (the left hand side of the equation) minus the gain from search (the last term on the right hand side) must be equal to the average creation cost $\frac{c}{q(\theta)}$.

The job destruction (henceforth JD) curve 19 implies that the reservation productivity net of the option value of the job is equal to the total workers' costs. The curve is upward sloping in the space R, θ . A higher θ reduces the option value of the job because it implies more job destruction: a searching worker is more likely to find a job and quit. A higher θ also increases the expected returns from search and therefore more search is undertaken and a job is more likely to be destroyed. This also reduces the option value of a job. The crossing of the JC and JD curves determines the equilibrium R and θ .

4.5 The Effects of a Mean-Preserving Spread

A mean-preserving spread h shifts the JC curve 18 outwards. The intuition is that the mean-preserving spread makes productivities above the mean better and productivities below the mean worse. Since workers and firms do not consider productivities below the job destruction threshold R (because jobs below R are destroyed anyway), the benefits from productivities above the mean outweigh the costs from productivities below the mean. Therefore firms create more vacancies because their expected gain from job creation increases more than the costs

(i.e. θ is higher) and workers search more because the expected rewards from search are higher (i.e. the range $[R, S]$ is wider). In contrast to the JC curve, a higher h shifts the JD curve in an uncertain direction, therefore the effect on the reservation productivity R (and on unemployment $u = \frac{\lambda R}{\lambda R + \theta q(\theta)}$) is in principle ambiguous. However in the calibration exercise we will see that, if the effect of the multiplicative shock is large on market tightness and small on job destruction, it is more likely that the steady-state level of R and u will fall.

In conclusion a mean-preserving spread of the productivity distribution $G(x)$ has two unambiguous effects which are derived in the Appendix: more people search (i.e. $(\frac{dS}{dh} - \frac{dR}{dh}) > 0$) and there are more vacancies (i.e. $\frac{d\theta}{dh} > 0$) which in turn implies that more seekers find new jobs and leave the stock of job seekers. As a result, the effect on the fraction of job seekers $\frac{e}{1-u}$ in Equation 16 is ambiguous because the mean-preserving spread increases both the numerator and the denominator, however, the effect on the job-to-job turnover rate $\frac{\theta q(\theta)e}{1-u}$ is positive.

The original contribution of this paper is the extension of the model to the analysis of the variance of the wages of job changers and job stayers after a mean-preserving spread in productivity shocks. Job changers are those among the job seekers in the range $[R, S]$ who have found a new match with probability $\theta q(\theta)$. Job changers are the job seekers with density $g(x)$ over $[R, S]$, therefore the variance of their wages is:

$$\text{var}\{w_{\text{changers}}(x)\} = \theta q(\theta) \text{var}\{w^s(x) \mid R < x < S\}. \quad (20)$$

The variance of wages across job changers unambiguously increases after a mean-preserving spread, because the range of productivities in $[R, S]$ increases. All job changers go from a job with productivity in $[R, S]$ to a new job with productivity $x = 1$ because all vacancies enjoy maximum productivity by assumption. The only meaningful wage variance of job changers is therefore the variance of wages before the job change, or alternatively the variance of the wage change $\text{var}(w_{\text{new}} - w_{\text{old}})$ given that $w_{\text{new}} = w^{ns}(1)$ for everybody. From this point of view, there is a clear connection with the empirical model of the variance of wage changes of Section 2.

Job stayers are those job seekers in $[R, S]$ who did not find a job, plus all non-seekers in the range $(S, 1]$. Job stayers have density $f_s(x) = (1 - \theta q(\theta)) \frac{g(x)}{I}$ over $[R, S]$ and $f_{ns}(x) = \frac{g(x)}{I}$ over

$(S, 1]$ where $I = \int_R^S (1 - \theta q(\theta))g(x)dx + \int_S^1 g(x)dx = 1 - \theta q(\theta)S - (1 - \theta q(\theta))R$. Hence:

$$\begin{aligned} \text{var}\{w_{stayers}(x)\} &= \left(\int_R^S w^s(x)^2 f_s(x)dx + \int_S^1 w^{ns}(x)^2 f_{ns}(x)dx \right) - \\ &\quad - \left(\int_R^S w^s(x) f_s(x)dx + \int_S^1 w^{ns}(x) f_{ns}(x)dx \right)^2. \end{aligned} \quad (21)$$

The change in the variance of the wages of the job stayers has an ambiguous sign since the mean-preserving spread increases the range $[R, S]$ but at the same time reduces the range $(S, 1]$.

In conclusion this model shows that an increase in the variance of x –which embodies increasing firm heterogeneity– leads to more search and more wage dispersion across job changers. There is a two-way relation between wage dispersion and on-the-job search. Wage dispersion is an incentive for low-paid workers to search on-the-job and more search in turn leads to increased wage dispersion for the following two reasons. First, wages at the low end of the distribution are lower when on-the-job search occurs because employed job seekers are paid less because they share the expected benefit of search with their employers through the wage bargaining. Secondly, because firms pay lower wages, they post more vacancies and induce more workers to search for better jobs. Thus on-the-job search and wage dispersion are mutually reinforcing, consistently with the literature that works with wage posting models and considers on-the-job search as an important source of wage dispersion (Burdett and Mortensen 1998; Bontemps et al. 2000; Christensen et al. 2005).

5 Calibration

In this section, I present the results of simulating a calibrated version of the model and examine its properties. In particular, I will assess the impact of a mean-preserving spread (henceforth MPS) and of a non mean-preserving spread (henceforth NMPS) of the distribution of productivity shocks on job turnover and on the wage variance of job stayers and job changers.

To connect the empirical and the theory sections, the parameter that governs the increase in the variance of the distribution of productivity shocks is calibrated using the estimates of the variance of the match shocks obtained in the empirical section. The model is simulated for values of h between $h = 0$ and $h = 0.2$, where h represents the parameter that governs the MPS of the distribution of shocks (since the distribution is over the unit interval, $h = 0.2$ represents a

TABLE 5. Parameters of the Calibration

Standard parameters: Shimer (2005)

$q(\theta) = A\theta^{-0.72}$		Matching function
A	1	Matching efficiency
r	0.01	Intertemporal discount rate
β	0.72	Workers bargaining power
λ	0.1	Separation rate

Internally calibrated parameters

c	0.25	Flow cost of vacancy
z	0.38	Unemployment benefit
σ	0.22	Search cost

Notes: c , σ and z are calibrated to target plausible values of the thresholds R , S and of the unemployment rate u . See the text for details.

20% increase in the variance). The increase of 20% is intended to reflect the estimated increase in the variance of the match component of wages (relative to the increase in the total variance) in the PSID (+23% between 1978 and 2005) and in the SIPP (+26% between 1993 and 2008).¹⁶

In order to perform the calibration, I calibrate the arrival rates of various events as quarterly rates and choose parameter values in line with the literature. I assume that the matching function is Cobb-Douglas $q(\theta) = A\theta^{-\alpha}$ and largely preserve the parameters provided by Shimer (2005). I set the matching function elasticity parameter $\alpha = 0.72$ (Shimer obtains this number when regressing the job-finding rate on labor market tightness at quarterly frequencies) and, as is standard in the literature, I set the household bargaining power β to be equal to the elasticity of the matching function α so as to fulfill the so-called Hosios condition. Furthermore I set the interest rate $r = 0.01$, the separation shock $\lambda = 0.1$ and I normalize the matching efficiency at $A = 1$.¹⁷ In the robustness checks at the end of this section, I will consider how different values of these four parameters –changing one of them at the time– affect the model’s results.

I calibrate the vacancy cost c , the opportunity cost of work z and the cost of search σ to pin down plausible values of the thresholds R , S and of the unemployment rate u . To target an unemployment rate of 6% and an unemployment inflow rate ($\lambda R(1 - u)$) of 5%, I set $R = 0.6$.

¹⁶This increase seems to be consistent with other evidence from other sources, for example, Comin and Philippon (2006) report an increase in the variance of firm level wages of 10% to 20% over 20 years –depending on the measure used.

¹⁷Shimer (2005) shows that there are infinite combinations of the scaling parameter of the matching function with the vacancy cost that leave the equilibrium rate of vacancies to the unemployment rate unchanged.

Together with $A = 1$ this implies a labour market tightness $\theta = 0.84$. I further target $S = 0.95$, which means that 5% ($\lambda(S - R)/(\lambda + \theta q(\theta))$) of employed workers search for jobs.¹⁸

The resulting parameters are in the lower part of Table 5: $c = 0.25$, $z = 0.38$ and $\sigma = 0.22$. Overall there is a close comparison with the previous literature: Shimer (2005) calibrates the first two at $c = 0.23$ and $z = 0.4$ while Burgess and Turon (2010) obtain a search cost $\sigma = 0.11$.¹⁹

Table 6 shows the results of the calibration of the model. Column (1) of the table shows the solution of the model with the parameters above and $h = 0$ (before the MPS): $R = 0.6$, $(S - R) = 0.35$, $u = 0.06$, $\theta = 0.84$, standard deviation ($w_{changers}$) = 0.073, standard deviation ($w_{stayers}$) = 0.074 and a job-to-job turnover rate of 3.2%.

These numbers fit fairly well some stylized facts of the labor market: they imply that the flow out of unemployment into new jobs $\theta q(\theta)u = 0.03$ and the flow of job-to-job transitions are $\lambda(S - R)\theta q(\theta) = 0.02$ which means that job-to-job movements are quantitatively important. This is consistent with the existing literature: in US data, between 50%-60% of job transitions do not involve a spell of unemployment, for example Bowlus and Robin (2004) report that 44% of the job-transitions of younger males in the NLSY79 data are direct job-to-job moves. Differently from unemployment and job-to-job turnover, the calibrated value of the variance of wages in the model cannot match the actual PSID or SIPP data because the formulas of the variance of wages (and of the wage levels) depend on the values of the other primitive parameters of the model (see Equations 20 and 21). The aim of the model, however, is not to match the variance of wages of job changers at a fixed point in time but its evolution relative to that of job stayers. Since, given these parameters' values, Equations 20 and 21 yield small numbers for the variance of wages, I prefer to show the standard deviation in Table 6 and in the following tables and figures.

Column (2) of Table 6 shows the results after a MPS of the distribution of productivity shocks. A MPS of $h = 0.2$ reduces the job destruction threshold R (the JD curve 19 moves

¹⁸There is very scant evidence on the extent of on the job search, mostly from Britain (Pissarides and Wadsworth 1994; Longhi and Taylor 2014). Hence there is no guidance as to the exact values of R and S , however if I target extreme values, the model yield inconsistent results. If I reduce the initial value of R below 0.4 then z (the opportunity cost of work) is negative. If S is above 0.95 then the increase in the variance of wages of job stayers increases more than the variance of job changers because the MPS barely increases the range $(S - R)$.

¹⁹There is a debate on the appropriate values for the replacement ratio z and workers bargaining power β . Whilst Shimer (2005) sets z to 0.4 and β to 0.72 to show that the model with Nash bargaining cannot deliver the volatility of unemployment and vacancies seen in the data, Hagedorn and Manovskii (2008) set the values of 0.95 and 0.05, respectively, and find much larger fluctuations of unemployment and vacancies within the same framework.

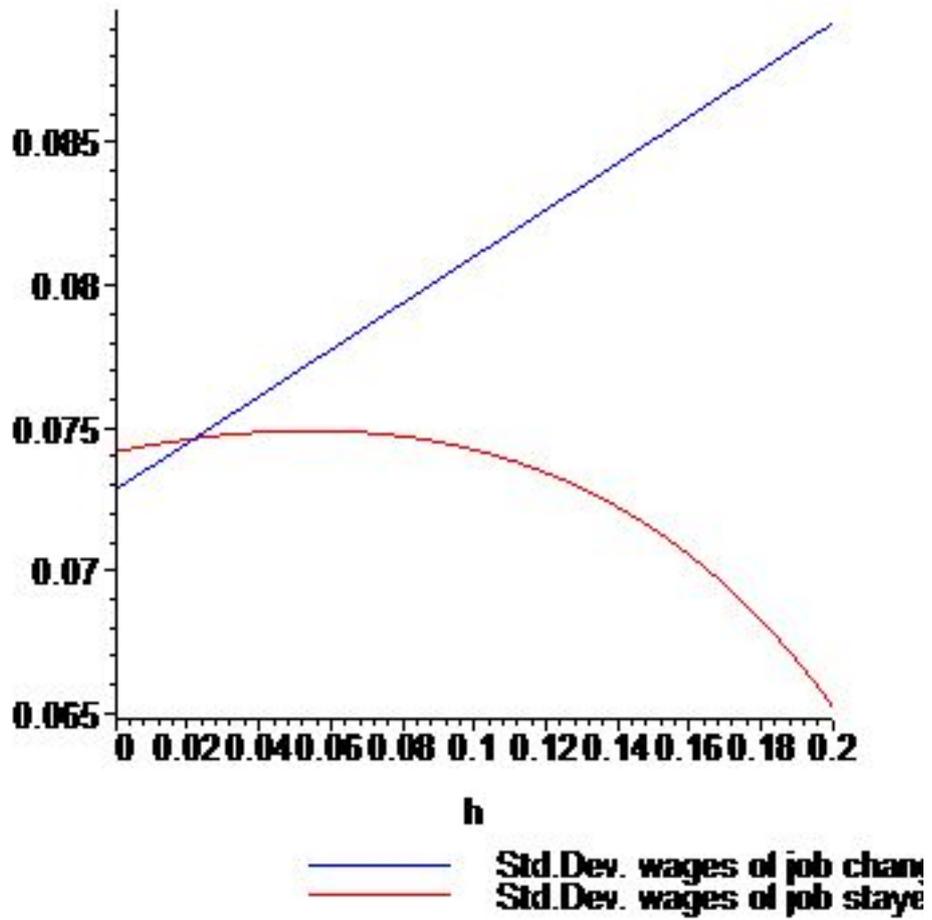


FIGURE 4. Standard deviation of wages of job changers and job stayers as a function of h .

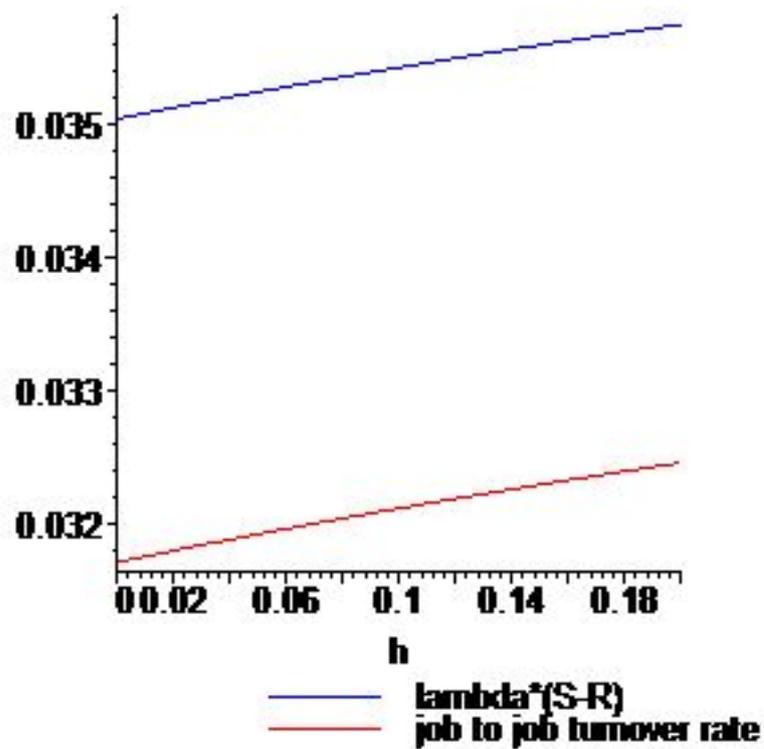


FIGURE 5. The range of on-the-job search and job-to-job turnover rate as a function of h .

out more than the JC curve 18 with these parameters) and increases, as expected, the range $(S - R)$ and market tightness θ . Thus the MPS implies an increase in on-the-job search and in the job-to-job turnover rate $\frac{\theta q(\theta)e}{1-u}$ (+6%), which translates into an increase in the standard deviation of wages for job changers (+23%) and a decrease in the standard deviation of wages for stayers (-12%) –numbers in parentheses in Table 6 indicate the percentage change with respect to the values in column (1).

Table 6 shows that this simple model can reproduce some of the patterns in the data that we have observed earlier in the empirical section: an increase in the variance of wages of job changers rather than job stayers. The increase in the variance of wages of job changers is of plausible values (similar to the increase in the variance of wage changes in Figure 1) while the decrease in the wage variance of stayers is implausibly large. However, the explanation of this large effect is in Figure 4: at first the standard deviation of wages of stayers increases with h , and start decreasing only at high values of h , i.e., for large shocks to the variance of the productivity distribution.

Figure 4 shows the standard deviation of wages for various values of h : the standard deviation of wages of job changers increases monotonically with a MPS while the standard deviation of wages of job stayers declines at high values of h . This happens because the variance of wages of job stayers depends on two factors (as explained in the comments to Equation 21): job stayers are those job seekers in $[R, S]$ who did not find a job (this term increase with h) plus all non-seekers in the range $(S, 1]$ (this term decreases with h). At high values of h , the decrease in the number of non-seekers is larger than the increase in the number of job seekers in $[R, S]$ who did not find a job.²⁰

Figure 5 plots the range of productivities which gives rise to on-the-job search $\lambda(S - R)$ and job-to-job turnover rate $\frac{\theta q(\theta)e}{1-u}$ for variable h . Both variables increase monotonically with h (the unemployment rate declines monotonically with h but it is not shown in the figure for convenience). The range $(S - R)$ determines –together with θ – both the share of employed job seekers $\frac{e}{1-u}$ and the share of job seekers who find a job, i.e., the job-to-job turnover rate. I plot the effect of an increasing h on $\lambda(S - R)$ to keep separate the effects of a MPS on the range $(S - R)$ from its effects on θ .

²⁰The figure shows the simulated standard deviations for fixed threshold $R = 0.6$ and variable h , hence the slightly different values with respect to Table 6 (where h is fixed and R varies).

Figure 5 and column (2) of Table 6 show that a MPS increases job-to-job turnover (column (2) of Table 6 indicates a 6% increase). This result is not entirely consistent with the evidence of a stable level of job turnover over time mentioned in the Introduction. To the extent of improving the fit of the model along this dimension, column (3) of Table 6 shows the effect of a non mean-preserving spread (NMPS) of the shock distribution on the outcomes of interest. Besides an increasing variance ($h = 0.2$), column (3) assumes an increase in the mean \bar{x} of the distribution from 0.5 (the mean of the uniform distribution over the range $[0,1]$) to 0.6 and could be viewed as the reflection of the increase in real average wages –an increase of 20%, equal to the increase in the variance. Higher wages imply that firms post less vacancies and therefore that there is a higher unemployment rate and a lower market tightness with respect to the situation of column (2). This in turn implies that the job turnover rate does not increase, consistently with the empirical evidence of the 1990s and early 2000s. Column (3) of the table shows that a NMPS leaves the job-to-job turnover rate unchanged with respect to the initial situation of column (1) while there is still an increase of the standard deviation of the wages of job changers (+22%). The same column also shows that a NMPS leaves the job destruction threshold R unchanged (in this case both the JD curve 19 and JC curve 18 move outwards) but still the range ($S - R$) increases.

In conclusion, it is the increase in the extent of on-the-job search (the range ($S - R$)) which governs both the number of employed job seekers and the their variance of wages. This feature of the model allows to generate higher wage instability because of a higher search activity on-the-job coupled with an increase in the variance of wage changes upon job change.

5.1 Robustness

Table 6 and Figures 4 and 5 show the simulated results obtained with plausible parameters values, but the model can predict this pattern of results for a constellation of parameters. In Table 7, I test the sensitivity of the results changing one parameter at the time and keeping all other parameters fixed at their benchmark values. I let four parameters vary, one at the time: the elasticity of the matching function a (and the bargaining power β assuming the Hosios conditions hold), the interest rate r , the arrival rate of shocks λ and the matching efficiency A .

Each column of Table 7 shows the value of the only parameter that changes with respect

TABLE 6. The Effects of a Mean-Preserving Spread and of a Non Mean-Preserving Spread

Variable		(1)	(2)	(3)
		$\bar{x} = 0.5$ $h = 0$	MPS $\bar{x} = 0.5$ $h = 0.2$	NMPS $\bar{x} = 0.6$ $h = 0.2$
R	Job destruction threshold	0.6	0.58 (-3%)	0.6 (0%)
$S - R$	Search range of productivities	0.35	0.38 (10%)	0.36 (3%)
θ	Market tightness	0.84	0.97 (15%)	0.95 (13%)
u	Unemployment rate	0.06	0.055 (-8%)	0.057 (-5%)
$\frac{\theta q(\theta)e}{1-u}$	Job to job turnover	0.032	0.034 (6%)	0.032 (0%)
$Std.Dev.(w_{stayers})$	Std. Dev. wages of stayers	0.074	0.065 (-12%)	0.066 (-11%)
$Std.Dev.(w_{changers})$	Std. Dev. wages of changers	0.073	0.090 (23%)	0.089 (22%)

Note: Results are obtained solving the model using the parameters of Table 5 and a uniform distribution $G(x)$ with support $[0,1]$. The mean-preserving spread is modeled as a parametric change $x(h) = x + h(x - \bar{x})$. Columns (2) and (3) show respectively the results of a mean-preserving spread (MPS) and of a non mean-preserving spread (NMPS) of the uniform distribution. Numbers in parentheses indicate the percentage increase with respect to column (1).

to the benchmark parameters of Table 5. For each new combination of the parameters, I recover the vacancy cost c , the opportunity cost of work z and the cost of search σ which are compatible with the target values of $R = 0.6$, $S = 0.95$ and $\theta = 0.84$ and then simulate the results of the main variables of interest (the endogenous variables): the standard deviation of wages of changers and stayers, unemployment and job-to-job turnover.²¹ Each row of the table refers to the change in an endogenous variable of interest. I simulate the results twice, before and after the MPS (as I did in Table 6), and each cell of Table 7 shows directly the difference of the simulated values of each variable in the form ‘value after the MPS- value before the MPS’ and the percentage change in parentheses. The same robustness exercise can be done with the NMPS but it not shown for reasons of space.

Table 7 contains two pieces of information: the first piece refer to the different value (with respect to the benchmark results of Table 6) of each variable of interest simulated before the MPS, the second piece refer to the percentage increase after the MPS (which of course could still be different from the results of Table 6). A higher arrival rate of shocks $\lambda = 0.15$ yields a higher unemployment rate (0.087 vs. 0.06) and a higher job-to-job turnover (0.047 vs. 0.032) before the MPS with respect to the results of Table 6, but the same percentage change in the standard deviation of wages of job changers with respect to the initial value before the MPS (+23%). This is somewhat expected because λ increases directly both the unemployment rate and job-to-job turnover, but its effect on the change of the variables after the MPS are not easy to predict. A lower $a = 0.62$ (and β by the Hosios conditions) yield a lower initial value of the wage variance of both stayers and changers and a larger increase in the standard deviation of wages of job changers. A higher interest rate $r = 0.02$ gives similar results to the benchmark. All simulations yield an increase (in different percentages) in the wage variance of wage changers, an increase in job-to-job turnover and a decrease in unemployment. The stability of the results, at least at the qualitative level, support the general validity of the model in the neighborhood of these values of the parameters. Of course if we move away from these parameters, the model can give different predictions. In the last column of the table a lower value of the matching efficiency $A = 0.8$ yields a wage variance of job stayers which is larger and rises as much as the wage variance of job changers, in contrast with the benchmark

²¹I target market tightness θ rather than unemployment to measure the effects of parameters’ changes on equilibrium unemployment.

TABLE 7. Robustness. The Effects of a Mean-Preserving Spread

Change in endogenous variable	Parameters' changes with respect to the benchmark			
	$\lambda = 0.15$	$a = \beta = 0.62$	$r=0.02$	$A = 0.8$
$\Delta \frac{\theta q(\theta)e}{1-u}$	0.051-0.047 (+9%)	0.033-0.03 (+10%)	0.034-0.03 (+13%)	0.027-0.025 (+8%)
Δu	0.085-0.087 (-2%)	0.057-0.06 (-5%)	0.057-0.062 (-8%)	0.07-0.071 (-1%)
$\Delta Std.Dev.(w_{stayers})$	0.055-0.073 (-24%)	0.057-0.067 (-15%)	0.063-0.073 (-13%)	0.115-0.091 (+26%)
$\Delta Std.Dev.(w_{changers})$	0.090-0.073 (+23%)	0.080-0.063 (+27%)	0.089-0.074 (+20%)	0.091-0.073 (+25%)

Note: Each column indicates the parameter –one at the time– that changes with respect to the benchmark values which are $\lambda = 0.1$, $a = \beta = 0.72$, $r = 0.01$ and $A = 1$. The calibration is in two steps: first c , σ and z are obtained targeting $R = 0.6$, $S = 0.95$ and $\theta = 0.84$ and then the equilibrium is solved with $h = 0$ (before the MPS) and $h = 0.2$ (after the MPS). Each cell shows the difference in the value of the simulated variable before and after the MPS (in the format ‘after-before’) and the percentage change in parentheses.

results. The model is sensitive to the value of the matching efficiency because A determines –together with θ – the probability of finding a job and the share of job changers and job stayers. A low value of A implies *ceteris paribus* that fewer job seekers find a match and become job changers, therefore more of them remain job stayers and their wage variance is higher.

6 Conclusions

The contribution of this paper is its assessment of the role of job changers in explaining the rise in earnings instability. An error component model shows that the increase in the estimated variance of the mobility component of earnings (the difference of two match effects in two different jobs) explains around 23% of the increase in the total variance of wage changes in PSID data and a similar share in SIPP data. These results suggest the value of studying the factors that produce the divergence of firm-level earnings, such as productivity shocks.

I show that it is actually possible to generate inequality across job changers within a standard

on-the-job search model if one applies a MPS of the distribution of productivity shocks. The MPS increases both on-the-job search activity and the wage variance across job changers: workers search more because of the higher option value of a change and, when they change jobs, their wage changes are larger because the distribution of shocks is more dispersed. Consistently with the empirical evidence, the model predicts a larger increase over time in earnings instability for job changers than for job stayers. The model is also able to reconcile the evidence of increasing instability with that of a stable level of job turnover. To obtain a stable turnover over time it is necessary to apply a non mean-preserving spread of the productivity distribution. The calibration of the model shows that these results are valid for a wide and reasonable range of parameters.

This paper complements other explanations of instability based on the rapid depletion of skills of the unemployed (Violante 2002; Hornstein et al. 2011) and is consistent with the findings obtained in the literature which estimates structural models. For example, Flabbi and Leonardi (2010) show that an increase in mobility (the job offer arrival rate in a model with on-the-job search) increases the cross-sectional variance of earnings in the U.S., thus suggesting – although with other methods – that there is a role for job mobility in explaining instability.

There are several avenues for further research. The first would head towards incorporating job change in error component models, and thus trying to model mobility decisions (along the lines of Cappellari and Leonardi 2015, or Hospido 2012). The second would be to build on-the-job search models that do not assume stationarity, thus obtaining a more appropriate description of labor markets evolving over time (along the lines of Bowlus and Robin 2004). A third possible improvement is to study specifically the role of mobility across occupations and industries (Kambourov and Manovskii 2008, 2009).

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A Data Appendix

A.1 PSID Data

The 1970–2007 PSID core individual file (after dropping the Latino sample) contains information on 58,663 individuals. Dropping those individuals who are never heads of their household between 1976 and 2007, the sample is reduced to 20,979 individuals. Keeping only those who are continuously heads of their household, have a non-missing education record and are aged 25 to 60 over this period leaves us with a sample of 17,053 individuals. I then drop female heads and remain with a sample of 11,751 male heads. I also drop non-continuous and outlying earnings records, eliminating the first and last percentile of earnings in each year. The sample then includes 10,340 individuals. I finally drop those records with missing tenure information and keep individuals with at least two continuous years of earnings (because the model is in first differences): the final unbalanced panel sample includes 8,119 individuals and 71,786 observations. The earnings variable is ‘head of household’s money income from labor’ i.e. the labor portion of money income from all sources: wages, bonuses, overtime, commissions, professional practice and the labor part of farm and business income. The nominal measure of earnings is deflated by the GNP personal consumption expenditure deflator with base year 2000 and divided by the annual hours worked to produce the real hourly wage variable used in the text.

A.2 SIPP Data

Each SIPP panel is a nationally representative sample of individuals interviewed once every four months for a certain number of times (from a minimum of 9 in 1993 to a maximum of 16 times in 2008; the 1996, 2001 and 2004 panels have 12 interviews). At each interview, respondents are asked to provide information covering the four months since the previous interview. The four-month span is the reference period for the interview, therefore somebody who responds to 9 interviews has 36 months of data. SIPP interviews each member of the survey households, I keep males aged between 25 and 60 who have 36 or more months of data (because three years of data is the minimum to estimate the model of Section 2). I drop the self-employed, those who are recalled by their previous employer after a separation, those with outlier earnings changes of more than 250% or less than 75% from one year to the next. I keep the same selection across all survey panels (1993, 1996, 2001, 2004 and 2008) to make the results comparable across years. The earnings and hours information is on a monthly basis and it is specific to each job. I annualize the earnings and hours information (summing monthly earnings and hours) at each job to make it comparable to PSID data. The hourly wage in each job is obtained by dividing annual earnings earned at the firm by annual hours worked at the firm. In case of multiple jobs at the same time I use only the main job (the one that pays the highest proportion of annual earnings). These criteria are used in Low et al. (2010) on the 1993 SIPP panel.

B Estimation Appendix

In this Appendix I briefly discuss the estimation of the match shock in models in first differences and in levels using PSID data. For reasons explained in Section 3 I use two-year differenced PSID data (to make PSID data consistent pre- and post-1997 and to avoid mismeasurement of annual income in the year of the job change). The following model adapts the one-year differenced model (Equation 2 in the text) to two-year (residual) earnings differences:

$$g_{it} = r_{it+2} - r_{it} + e_{it+2} - e_{it} + I(M_{it} = 1)(a_{ijt+2} - a_{ijt}), \quad (22)$$

with moments:

$$\text{cov}(g_{it}, g_{it}) = \sigma_{z_{t+2}}^2 + \sigma_{z_{t+1}}^2 + \sigma_{e_{t+2}}^2 + \sigma_{e_t}^2 + I(M_{it} = 1)\sigma_{\phi_{t+2}}^2 \quad (23)$$

$$\text{cov}(g_{it}, g_{it-2}) = -\sigma_{e_t}^2 \quad (24)$$

where the only difference with the one-year differenced model is that the permanent shock cumulates over two years. If the worker is a job changer (i.e. $M_{it} = 1$) I assume that that workers have changed job only once during the two-year period and the mobility shock ϕ_{it} is the same when taking one-year or two-year differences in the match component $a_{ijt+2} - a_{ijt}$.

I estimate the model parameters using the Equally Weighted Minimum Distance estimator (EWMD) which matches moment restrictions generated by the earnings model with empirical moments obtained from the data. I use and a robust variance estimator $\text{Var}(\theta) = (G'G)^{-1}G'VG(G'G)^{-1}$, where θ is the parameter vector, V is the fourth moments matrix and G is the gradient matrix evaluated at the solution of the minimisation problem. The number of individuals used in estimation is 7,114 and the number of cross-products (variances and first-order covariances) is 88,094. Table 2 in the text shows the results from the estimation of this model year by year. This same model estimated on the pooled PSID sample 1976–2007 gives the following results: $\sigma_z^2 = 0.016(0.002)$; $\sigma_e^2 = 0.041(0.001)$ and $\sigma_a^2 = 0.065(0.002)$.

In the literature on earnings instability there is a debate on model estimation in wage levels rather than in wage differences (Moffitt and Gottschalk 2012). The equivalent model estimated in levels has the following form:

$$u_{ijt} = r_{i0} + \sum_{s=1}^t z_{is} + a_{ij} + e_{ijt} \quad (25)$$

where u_{ijt} is an estimated residual from a standard log wage regression. Residual wage income in period t is the sum of the initial level of permanent income at the start of the sample $r_{i0} \sim (0, \sigma_{r0}^2)$ representing an unobservable endowment or initial condition, past and contemporaneous permanent income shocks, a time-invariant match component a_{ij} and a i.i.d. residual e_{ijt} . Those who support estimation in differences (e.g. Blundell et al. 2016) claim that first differences remove the initial condition r_{i0} and are therefore robust to the many cases in which the initial condition is correlated with the path of permanent shocks. If, for example, individ-

uals who invest a lot in human capital early on -and therefore have lower initial conditions- are compensated by a path of permanent shocks that is above average (as in random growth models, see for example Guvenen et al. 2014), then $cov(r_{i0}, z_{is}) < 0$ for all s and the estimate of the the variance of permanent shocks σ_z^2 obtained from level moments would be downward biased.

To avoid the initial condition problem let us take a simpler model in levels which contains a time-invariant worker fixed effect r_i instead of a random walk (as for example in Parent 2002):

$$u_{ijt} = r_i + a_{ij} + e_{ijt}. \quad (26)$$

This model yields the following cross products to fit the covariance structure model:

$$cov(u_{ijt}, u_{ijt}) = \sigma_r^2 + \sigma_a^2 + \sigma_e^2 \quad (27)$$

$$cov(u_{ijt}, u_{ikt-s}) = \sigma_r^2 + I(j = k)\sigma_a^2 \quad (28)$$

where $I(j = k)$ indicates the same job and is equivalent to the notation $M_{it} = 0$ used in this paper. This model estimated on the pooled PSID sample 1976–1997 (after 1997 the PSID becomes biannual and the job changer indicator does not identify changers) gives the following results: $\sigma_r^2 = 0.153(0.005)$; $\sigma_e^2 = 0.069(0.003)$ and $\sigma_a^2 = 0.021(0.006)$.

Comparing the results of the two models, the estimate of the variance of the match component (σ_a^2) is larger when the model is estimated in differences (two-year differences). However it is common to estimate parameters of different magnitudes when the specification is in levels rather than changes. Usually models in levels estimate a lower permanent shock and a much higher trasitory shock (Manovskii et al. 2011) and the estimates tend to converge when the first and last observations of each individual are eliminated (as they are more volatile). In my paper there is an substantial reason to estimate the model in differences: since the PSID records annual earnings, the change in earnings consequent to a job change cannot be exactly measured and earnings during the year of the job change are a mixture of the earnings from the old and the new job. For job changers in year t , the problematic income which mixes earnings in the two jobs is recorded in $t + 1$ (the PSID survey in $t + 1$ records the annual income of the previous year). To avoid this problem, I take two-year differences in log earnings ($logw_{it+2} - logw_{it}$).

C Model Appendix

This Appendix derives the effects of a mean-preserving spread on the model. The model is solved with a uniform distribution and the mean-preserving spread is a parametric change $x(h) = x + h(x - \bar{x})$ considering the effect of a marginal dh at $h = 0$. This Appendix shows that $\frac{dS}{dh} - \frac{dR}{dh} > 0$ and $\frac{d\theta}{dh} > 0$ using the total differential of equations 17, 18 and 19.

The total differential of the JD curve Equation 19 can be written:

$$\left(1 + \frac{d\Lambda}{dR}\right) \frac{dR}{dh} = \bar{x} - R - \frac{d\Lambda}{dh} - \frac{d\Lambda}{d\theta} \frac{d\theta}{dh} \quad (29)$$

The mean-preserving spread has three effects on R : it increases R directly if $\bar{x} > R$, it increases R through market tightness θ , it decreases R by increasing the option value of a job.

The option value of a job can be written:

$$\begin{aligned} \Lambda(R, \theta, \sigma, h) &= \lambda \int_R^1 \max(J^{ns}(s), J^s(s)) ds = \lambda \int_R^S J^s(s) ds + \lambda \int_S^1 J^{ns}(s) ds = \quad (30) \\ &= \lambda(1 - \beta)(1 + h) \left[\frac{1}{r + \lambda + \theta q(\theta)} \int_R^S (x - R) ds + \frac{1}{r + \lambda} \int_S^1 (x - R) ds \right] - \\ &\quad - \frac{\lambda(1 - \beta)}{r + \lambda} \left(\frac{\beta}{1 - \beta} c\theta - \sigma \right) (1 - S) \end{aligned}$$

$$\frac{d\Lambda}{dR} = \lambda(1 - \beta)(1 + h) \left[-\frac{1}{r + \lambda + \theta q(\theta)} (S - R) - \frac{1}{r + \lambda} (1 - S) \right] < 0 \quad (31)$$

$$\frac{d\Lambda}{d\theta} = -\frac{\lambda(1 - \beta)(1 + h)}{(r + \lambda + \theta q(\theta))^2} (q(\theta) + \theta q'(\theta)) \int_R^S (x - R) ds - \frac{\lambda\beta}{r + \lambda} c(1 - S) < 0 \quad (32)$$

$$\frac{d\Lambda}{dh} = \lambda(1 - \beta) \left[\frac{1}{r + \lambda + \theta q(\theta)} \int_R^S (x - R) ds + \frac{1}{r + \lambda} \int_S^1 (x - R) ds \right] > 0 \quad (33)$$

The reason $\frac{d\Lambda}{dh} > 0$ is the truncation of the productivity distribution at R . A mean-preserving spread increases the expected rewards from search because it makes productivities above the mean better and productivities below the mean worse, but workers and firms do not consider productivities below R .

The total differential of the JC curve Equation 18 reads:

$$\frac{(1 - R)(1 - \beta)}{r + \lambda} - \frac{1 - \beta}{r + \lambda} \frac{dR}{dh} = \left[\frac{c}{\theta q(\theta)} \eta + \frac{\beta c}{r + \lambda} \right] \frac{d\theta}{dh} \quad (34)$$

substituting 34 into 29 we obtain:

$$\frac{d\theta}{dh} \left[\frac{d\Lambda}{d\theta} - \left(1 + \frac{d\Lambda}{dR}\right) \left(\frac{r + \lambda}{1 - \beta} \frac{c}{\theta q(\theta)} \eta + \frac{\beta c}{1 - \beta} \right) \right] = \bar{x} - R - \left(1 + \frac{d\Lambda}{dR}\right) (1 - R) - \frac{d\Lambda}{dh} \quad (35)$$

the sign of $\frac{d\theta}{dh}$ is positive because both the RHS and the LHS of Equation 35 are negative since $-1 < \frac{d\Lambda}{dR} < 0$. The sign of $\frac{dR}{dh}$ from 34 is ambiguous.

Finally the total differential of Equation 17 with respect to h at $h = 0$ gives:

$$\frac{dS}{dh} - \frac{dR}{dh} = -(S - R) + \left[\frac{\beta}{1 - \beta} c \left(1 + \eta \frac{r + \lambda}{\theta q(\theta)} \right) + \frac{(1 - \eta)(r + \lambda)\sigma}{\theta^2 q(\theta)} \right] \frac{d\theta}{dh} \quad (36)$$

where $0 < \eta < 1$ is the elasticity of the matching function $q(\theta)$. Knowing that $\frac{d\theta}{dh} > 0$ and assuming $(S - R)$ small, the result of a mean-preserving spread is $\frac{dS}{dh} - \frac{dR}{dh} > 0$. This means that the range of productivities over which workers search on the job is larger and the range of productivities over which they do not search is smaller. A mean-preserving spread makes the gap between S and R larger because it increases θ and therefore increases the expected rewards from search.