Wage dynamics and labor market transitions: a reassessment through total income and "usual" wages.

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Abstract

We present a simple on-the-job search model in which workers can receive shocks to their employer-specific productivity match. Because the firm-specific match can vary, wages may increase or decrease over time at each employer. Therefore, for some workers, job-to-job transitions are a way to escape job situations that worsened over time. We use two independent measures of workers' compensation to provide a convincing identification strategy for the presence of a job-specific or employer-specific wage shock process. In the first measure, workers are asked about the usual wage they earn with a certain employer. In the second measure, workers are asked about their total amount of labor earnings during the previous year. While the first measure records the wages at a given point in time, the second measure records the sum of all wages within one year. We calibrate our model using both measures of workers' compensation and data on employment transitions. The results show that 59% of the observed wage cuts following job-to-job transitions are due to deterioration of the firm-specific component of wages before workers switch employers.

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1 Introduction

We use a particular feature of the National Longitudinal Survey of Youth (NLSY79) to uncover the evolution of workers' compensation over time. We study wage dynamics through a generalized search model in which workers can receive shocks to their productivity match. The specific feature of the survey that is most useful for us is that the dataset includes two independent measures of workers' compensation. In the first measure, workers are asked about the usual wage they earn with a certain employer (hereafter *wages*), for up to five employers per survey. In the second measure, workers are also asked their total amount of labor earnings during the previous year (hereafter *earnings*). While the first measure records the wages at a given point in time, the second measure records the sum of all wages within one year. For simplicity, we can think of the first measure as a time-dependent function evaluated at one point, while the second measure is the integral of such a function between two different points. We show how the simultaneous use of both measures can help in understanding the nature of the wage shock for employed workers.

In the first part of the paper, we study the relationship among earnings, wages, and employment transitions. We show that the standard job ladder model cannot reconcile wage dynamics and earnings dynamics across different labor market transitions in the U.S. We explore alternative explanations of that discrepancy through wages and earnings growth regressions across different labor market transitions using both NLSY79 and Survey of Income Participation (SIPP) data. We show that although the dynamics of wages are consistent with a job ladder model, the same is not true for the dynamics of earnings. While relatively large wage increases follow job-to-job transitions, we observe that job-to-job transitions are negatively correlated with hourly earnings. We speculate that this is due to the fact that job-to-job transitions are more likely to follow a large reduction in wages. We find that this result is robust to mis-measurement in the labor supply and disappears for workers paid by the year. The rationale for this last finding is that workers paid by the year are much less likely to be hit by "unobserved" wage shocks than other workers. We find that the most convincing hypothesis supported by the data is the existence of shocks to the firm-specific component.

Using the multiple measures of workers' compensation and data on employment transitions, we then calibrate a modified job ladder model that allows for shocks to the employer-employee match (as in Nagypal, 2005, and Jolivet, Postel-Vinay, and Robin (JPVR), 2006). In our model, job-to-job transitions move workers up the ladder, but they move relative to the last wage at each employer. Because the firm-specific match can receive shocks, wages may increase or decrease over time at each employer. Therefore, for some workers, job-to-job transitions are a way to escape job situations that worsened over time. We calibrate the parameters of the model using simulation-based methods. We simulate the data using our model to replicate the NLSY. We select some of the parameters using the NLSY sample that we replicate, and we identify the rest of the parameters using auxiliary models. The results show that it is important to include shocks to earnings to the standard job ladder model. In our calibration 59% of the observed wage cuts following job to job transitions are due to deterioration of the firm-specific component of wages before workers switch employers.

1.1 Literature Review

Topel and Ward (1992) initiated an extensive literature in empirical economics documenting the positive impact of job mobility on wages for young workers. In their seminal paper, they estimate that nearly a third of the total wage growth in the first 10 years of labor market experience is due to wage jumps at the time of changing a job. Although several empirical models have been used to study this phenomenon, the standard job ladder model is the workhorse for this literature[1].

Unfortunately, the job ladder model has several limitations in understanding wage dynamics and labor market transitions. Two primary issues have been identified: First, the model cannot reconcile the high rate of job-to-job transitions that exists even after workers have accumulated several years of seniority (Nagypal, 2005). Second, the job ladder model fails to explain the greater number of wage cuts for workers who switch employers (as opposed to those who remain with their current employer) (JPVR, 2006; Lopes de Melo, 2007). The latter problem can be mitigated by assuming that wages are observed with error (Flinn and Heckman, 1984; Wolpin, 1987). However, this shortcut does not explain why the fraction of wage cuts is larger for workers who experienced an employer change (without unemployment) than for job stayers (JPVR, 2006; Lopes de Melo, 2007). For example, in the NLSY79 sample of males, 31 percent of workers who switched employers accepted a reduction in their wage rate from one year to the next. The fraction was only 26 percent for workers who remained at their current employer.

An extension of the standard job ladder model that has been proposed to ameliorate these

[1] For a review, see Eckstein and van der Berg (2007).

failures is the introduction of a shock to the existing employer-employee match. The rationale behind this extension is that the employer-employee match might vary over time. These changes can be due to either idiosyncratic shocks to the firm's productivity or shocks to the value of the match between the worker and the firm. A corollary of this extension is that workers hit by a negative shock are more likely to leave their employer. However, the existing literature has not been able to provide a convincing identification strategy for such shocks.

In virtually all data sets, wages are not continuously observed but sampled at most only a few times a year. Therefore, changes in observed wages may hide the fact that between observations a worker has received a negative shock and decided to leave his employer. That is, the wages that a worker receives after changing jobs might be lower than the wage he received one year earlier but still be higher than the last "unobserved" wage he received in the previous job. In this direction, JPVR (2006) present a standard search model where in, every period, employed workers can receive up to two types of shocks in addition to the possibility of receiving an outside offer. Workers can receive, with probability δ, a standard job destruction shock. Workers can also receive, with a certain probability, a "reallocation shock." The reallocation shock is a job offer with a wage drawn from the unconditional wage distribution, which workers cannot reject unless they become unemployed (which by assumption is never preferable). This reallocation shock is equivalent to a layoff immediately followed by a job offer. JPVR argue that, as a matter of structural interpretation, this can be the result of an employer-provided outplacement program or from the worker's job search activity during the notice period. This reallocation shock allows the authors to make the model consistent with the (i) observed positive share of job-to-job transitions followed by a wage cut and (ii) nonstationary pattern for unemployed workers' re-employment rates. However, this shock is solely identified by the pattern of wage cuts (i.e., the authors are not able to provide additional empirical evidence of the presence of the reallocation shock).

Postel-Vinay and Turon (2010), and Lise, Meghir, and Robin (2013) proposed search matching models where, with some differences among them, they allowed matches between employers and workers to change over time. These changes allow for wage renegotiation, which might end in a wage cut for the worker. As in JPVR, in Postel-Vinay and Turon the within-job shock is solely identified by the pattern of wage cuts observed in the data. Lise, Meghir, and Robin (2013) use the within and between-job variance of wage growth to identify the rate of arrival of productivity shocks.

The rest of the paper is organized as follows. Section 2 presents the empirical analysis. We first describe the data and explain how we can reconstruct earnings. We then show that the patterns of the data cannot be rationalized through the standard job ladder model. After outlining how shocks to wages can rationalize the facts from the data, we present evidence that allows us to dismiss other alternative explanations for the patterns in the data. In Section 3 we outline the model. Section 4 explains the simulation and presents our calibration. Section 5 concludes.

2 The Empirical Analysis

2.1 The Data

We draw our sample from the NLSY79. The NLSY79 is a nationally representative sample of 12,686 young men and women who were 14 to 22 years of age when they were first surveyed in 1979. These individuals were interviewed annually through 1994 and are currently interviewed on a biennial basis. For our sample, we follow the standard criteria in the literature by restricting the sample to non-military men, at least 25 years old, who are not enrolled in school and do not own a business. We do not include the over-sample of blacks and poor whites. We also exclude any observation years in which the labor market history of the individual is not perfectly observed or in which individuals had more than one job at the same time (dual earners). The top part of Table 1 presents some characteristics of our final sample. The average man in our sample was 28.32 years of age and had 12.6 years of schooling and almost 8 years of potential experience. Black workers represent eleven percent of our sample.

A key feature of this survey is that it gathers information in an event history format, in which dates are collected for the beginning and ending of important life events. Labor force activity is detailed in this manner. Information includes the start and stop dates for each job held since the last interview, periods in which individuals are not working but are still with an employer, and labor market activities (looking for work, out of the labor force) during gaps between jobs. Using this information the NLSY constructed the Work History File, which provides the weekly labor market history of each individual over the whole sampling period.

Our main goal is to identify the dynamics of wages within and between employers. Thus, we pay particular attention to the two measures of labor compensation provided by the survey. The first one is *wages*. During each interview, a worker is asked how much he usually earns at each job, for up to five employers per interview, where "Usually is 50% of the time or more; or your most frequent schedule in the last 4 or 5 months." Wages include overtime, tips, and bonuses. The second measure of compensation is annual *earnings.* In this case, a worker is asked his "total income from wages and salary in the last calendar year." It is important to note that these two measures are independently collected at different moments of the interview and are not constructed using the same underlying information.

Note that the total labor earnings that a worker receives in a given year, excluding dual job holders, is simply the sum of all wages received, denoted as

$$E(t+1) = \int_t^{t+1} w(x)\, n(x)\, dx, \tag{1}$$

where $E(t+1)$ is earnings accumulated between t and $t+1$, $w(t)$ is wages at time t, and $n(t)$ is the labor supply of the worker at time t. Using both measures of labor income provides an additional tool with which to identify the wage process and rationalize the high fraction of wage cuts observed in the data. Although the econometrician observes neither the last wage paid to a worker before he changes employers nor the first wage following the switch, by using the mapping represented by equation (1), we can learn much about the evolution of the wages between t and $t+1$.

2.2 Constructed Earnings

Because wages and earnings are intrinsically different, we need a strategy that allows us to study their evolution concurrently. We follow a simple strategy: We make a simple assumption that allows us to use wages to construct earnings. We can compare the pattern of the resulting constructed variable with the one displayed by the true earnings. Any discrepancy will be necessarily attributed to the assumptions we have made.

We start by assuming that "usual" wages are equal to "average" wages (and "usual" hours worked in one job are equal to "average" hours). Suppose that a worker is interviewed at time $t+1$ and he is asked about his labor market history between t and $t+1$. Assume that the worker changed employers (without being unemployed) at time $t+\Delta$, where $0 < \Delta < 1$. During the interview, the worker reports the usual wage in the old job $\bar{w}_O$, the usual wage in the new job $\bar{w}_N$, and the usual number of hours worked in each job, $\bar{n}_O$ and $\bar{n}_N$, respectively. Under the assumption that average wages are equal to usual wages, we have

$$\begin{aligned}\bar{w}_O &= \frac{\int_t^{t+\Delta} w(x)\, n(x)\, dx}{\bar{n}_O \Delta}, \\ \bar{w}_N &= \frac{\int_{t+\Delta}^{t+1} w(x)\, n(x)\, dx}{\bar{n}_N (1-\Delta)}.\end{aligned}$$

It is easy to see that we can construct an alternative measure of all labor income received by the worker between t and $t+1$ using this information on usual wages. Such measure is equal to

$$CE(t+1) = \bar{w}_O \bar{n}_O \Delta + \bar{w}_N \bar{n}_N (1-\Delta).$$

This example has been written for the simple case of a worker who has experienced one job-to-job transition in a given year, but it can be easily generalized to all labor market transitions.

Under the assumption that "usual" wages are equal to average wages, $CE(t+1)$ and $E(t+1)$ should be identical. Although the presence of measurement error would break this equality, we should still expect that these two variables behave similarly over the life cycle of a worker and interact similarly with labor market transitions. The middle part of Table 1 presents the average hourly wages, hourly earnings, and hourly contructed earnings for our sample. Average labor earnings in our sample have slightly lower average growth than both average wages and average constructed earnings.

The assumption that average wages are equal to usual wages is a reasonable assumption if reality functions as described in Burdett and Mortensen (1998), where the job-specific component of wages does not change stochastically over time; but the assumption also could be consistent with a more general model in which the firm-specific component of wages evolves over time. In the next section, we show that, although this latter assumption seems reasonable, the constructed version of earnings fails to replicate the pattern that the true earnings display. We then show that this failure can be explained only by the existence of a job-specific shock and by the fact that "usual" wages are not necessarily equal to "average" wages, but rather are simply the most common wage paid to the workers in the last time period.

2.3 Wage Dynamics and Labor Market Transitions

A common result of search models is that workers switch employers voluntarily if and only if the option value associated with a new job exceeds the option value associated with remaining in the old job. In most cases (see, for example, Burdett and Mortensen, 1998), this is equivalent to comparing the existing wage with the potential wage in the new job and switching only if the latter is higher.[2] Ideally, to test this prediction, if the transition happens at $t+\Delta$, we would like to observe the wage in both jobs at time $t+\Delta$. Unfortunately, the econometrician never has such a rich information set. A researcher usually observes the wage in the old job only at time t and the wage of the new job only at time $t+1$. The NLSY has an advantage over other datasets because at time $t+1$, the survey asks retrospectively about the wage in the previous job. If a worker switches employers at time $t+\Delta$, the NLSY provides a measure of the worker's "usual" wage at the old job between t and $t+\Delta$ and a measure of the "usual" wage at the new job between $t+\Delta$ and $t+1$.

Under the assumption that wages are relatively stable during a survey year, we have shown in the previous section that we can construct labor earnings using wage information. If "usual" wages equal average wages, then earnings and constructed earnings should coincide. For example, if constructed earnings growth is higher for workers who have experienced a job-to-job transition than it is for job stayers, we would expect the same relationship to hold for earnings.

Table 2 presents the percentage change in real hourly earnings (HE) and hourly constructed earnings (HCE) of male workers between 25 and 65 years of age, conditional on the worker having had a job-to-job transition relative to those who stayed at the same job as the previous year for workers with different levels of education. The table shows that the growth in HEs is not as strongly positively correlated with job-to-job transition as is HCEs growth, a pattern that is present accross all education groups. For workers with up to a high school diploma, HE are negatively correlated with job-to-job transitions. Only workers with some college or more increased their HEs by an average of 2.6% in years when they switched employers, which still is below the 5.76% growth in constructed earnings. Instead, HE for workers who stayed in the same job grow at a faster rate than HCE.

To understand the observed patterns of the data, we next study the relationship among earnings, wages, and employment transitions. We start by assuming that wages evolve according to the standard search model, and then we present our hypothesis to explain this relationship. We also consider two alternative explanations which, like our hypothesis, can explain the discrepancy between earnings and wages across different labor market transitions: a mismeasured labor supply and better prospects.

[2] A notable exception is Postel-Vinay and Robin (2002).

2.3.1 Earnings and Wage Growth in the Standard Job Ladder Model

The standard job ladder model assumes that workers can search on the job and that employed workers leave their current job if, and only if, they are offered a higher wage. We assume that wage growth rates may depend on experience, calendar time, ethnic background, and educational level. In order to abstract from labor supply effects, in both the intensive and extensive margin, we normalize the working time between two interviews to be equal to 1. Hence, we consider hourly real wages and earnings. The change in earnings from one year to another is

$$\Delta E\left(t+1\right)=\int_{t}^{t+1}w\left(x\right)n\left(x\right)dx-\int_{t-1}^{t}w\left(x\right)n\left(x\right)dx$$

where the subscript indicates the survey period to which the variable refers. Assuming that wages are constant within employers between interviews, constructed earnings and observed earnings should be identical. For a worker who experienced a job-to-job transition between t and $t+1$ but otherwise stayed with the same employer, the change in earnings and constructed earnings should be equal to:

$$\Delta E\left(t+1\right)=\Delta CE\left(t+1\right)=\bar{w}_{O}^{t+1}\bar{n}_{O}^{t+1}\Delta+\bar{w}_{N}^{t+1}\bar{n}_{N}^{t+1}\left(1-\Delta\right)-\bar{w}_{O}^{t}\bar{n}_{O}^{t}$$

Using data on $\log CE(t+1)$ and $\log E(t+1)$, we next study whether there exists systematic differences between these two ways of calculating the same statistics. In Table 3, we report the coefficients of an OLS regression of log wages, log earnings, and log constructed earnings on the covariates and dummies for different labor market transitions. Although the estimated wage growth between t and $t+1$ is 4% higher for workers who experienced a job-to-job transition than for those that stayed at the same employer, the impact of job-to-job transitions on constructed earnings is around 2%. This is due to the fact that the higher wage has been received by the worker for only $(1-\Delta)$ periods. The interesting feature of the data is that, once we look at the true earnings, we see that job-to-job transitions are associated with an earnings decline of 7%. As we have previously mentioned, this disconnection between the two measures must be explained by the failure of one of the assumptions that we have made to calculate constructed earnings. Interestingly, the coefficients for transitions from job to unemployment to job are similar between the two measures of earnings. However, we should be more cautious in interpreting these coefficients given that, for example, we do not include in our calculation of constructed earnings any measure of severance payments.

What we learn from the previous results is that the standard job ladder model does not allow us to reconcile the measures of wages and earnings observed in the data. This implies that wages are not constant within an interview, that "usual" wages are not equal to "average" wages, and that "usual" wages are higher than average wages for workers who experience a job-to-job transition. To further test this hypothesis we run robustness checks.

First, we split the sample into workers that are paid by the hour and those that are paid by the year. We explore the dynamics in both groups: workers paid by the year versus workers paid by the hour. Because pay changes are less frequent for workers paid by the year, we expect to find less discrepancy between the two measures. The results are shown in Table 4. Among workers paid by the hour, those that switch employers experienced a 4% higher increased of their constructed earnings relative to those that stayed at the same employer. However, hourly earnings for those same workers that switch employers decreased on average 10% more than those workers that did not switch employers. For workers paid by the year, there are no significant differences in earnings and constructed earnings between workers that switched employers and workers that did not switch. The difference between both compensation measures is smaller (2 percentage points) than for workers paid by the hour (14 percentage points). That is, the difference in the dummy for job-to-job transitions is larger for workers paid by the hour and it disappears for workers paid by the year.

We also consider alternative agregations of the data. In order to calculate both measures of hourly earnings we rely on the weekly information provided by the NLSY. However, if a worker experiences unobserved unpaid working gaps between two adjacent jobs, we could overestimate constructed earnings and underestimate true hourly earnings. This sort of non-classical measurement error could replicate the patterns that we have seen so far. In order to address this concern we take a conservative strategy. To construct true hourly earnings we rescale this measure if the worker has experienced a job-to-job transition. The scaling factor assumes that the worker has been working a week less than reported. If the worker reports working for 54 weeks in a given year with a job-to-job transition, the scaling factor is $\frac{54}{53}$. Similarly we construct an additional measure of constructed hourly income that assumes that the worker has worked a week less than reported in the last job prior to a job-to-job transition. The results are reported in Table 5 and suggest that this correction is far from being enough to generate the observed difference between the two measures of hourly income, although the gap is slightly smaller when compared with Table 3. The difference between earnings and constructed earnings decreases from 9.3 percentage points in Table 3 to 5.2 percentage points in Table 5.

The empirical evidence we have provided is consistent with the following story: the job-specific component of wages is subject to shocks, therefore workers who experience a negative wage shock are more likely to change employers soon after the shock. This can also explain why usual wages are higher than average wages. The last wage paid by the employer might not be considered by the worker to be his usual wage because he left that employer relatively soon after such a change. This might also explain why we observe so many negative wage changes after job-to-job transitions.

In the next subsection we investigate whether the same pattern can be explained by alternative hypotheses.

2.3.2 Alternative Wage Dynamics

While it is obvious that the reason for the discrepancy between constructed and true earnings must be that "usual" earnings are not equal to average earnings, we now try to find explanations that could compete with our preferred story and we try to test whether they are indeed more likely to influence the results. An alternative to the shocks hypothesis is that workers might accept a wage cut because the option value of the new job is higher than the option value at their current employer. That is, workers accept a wage cut for better future career prospects (as in Postel-Vinay and Robin (2002)). This could simultaneously explain why we observe wage cuts and why earnings may be lower after a job-to-job transition. It could also explain the difference between constructed and true earnings, as long as the wage reported as "usual" is on average higher than the initial wage and the average wage.

In our explanation, wage cuts are a measurement problem and workers change employers only if their new wage is higher than the previous one. In this alternative story, workers instead actually accept a wage cut. Ideally, observing the very last wage in the old job and the very first wage in the new job would be enough to tell the two stories apart. Although this is not possible, we can look at an alternative data set to find additional evidence. The Survey of Income and Program Participation (SIPP) provides monthly labor income as well as hourly wages and hours worked month by month. Unfortunately, SIPP provides these data only for workers that are paid by the hour. This implies that we observe monthly wages for a worker that changed employers only if both employers paid the worker by the hour. This restriction doesn't allow us to use SIPP to study the dynamics of wages across labor market transitions, and it does not completely fix the data collection problem because even within a month, workers can be exposed to wage changes; but it does give us additional evidence to support one of the two alternative hypotheses.

We use 1996 panel from the SIPP and study the dynamics of monthly labor income for a sample of male workers between 25 and 60 years of age and we restrict our sample using the same criteria as in the NLSY79 sample. We run income growth regressions, as in the NLSY data, and in addition to contemporaneous labor market transitions we add dummies for future and past labor market transitions. We observe workers in opur panel during 48 months. For each period t, we look at his labor market transitions during the previous six months $(t-6)$ and the future six months $(t+6)$. If the worker switch employers in any of the subsequent six months $(t+6)$, the "JJ within the next 6 month" dummy will take value 1. This dummy allows us to identify how earnings growth behave before the switch occurred. Similarly of the worker switch employers in any of the six previous months $(t-6)$, the "JJ within the past 6 month" dummy will take value 1. In this case, the dummy identifies how earnings grow during th efirst 6 months at the new employer. We construct dummies accross Job-to-unemployment-to-job (JUJ) and layoff transitions following the same logic.

Table 6 presents the estimates, with standard errors in parentheses. Consistent with our story, workers who will experience a job-to-job transition in the next 6 months (on average) experience within-job wage growth 1% lower than those who stayed at the same job. The same pattern is present for different subsamples (young workers, workers with at most a high school diploma, and workers with at least some college education). The alternative hypothesis (workers accept an initial wage cut for a better career prospect) would predict that wages grow faster for workers who have just experienced a job-to-job transition. Interestingly, if anything, the opposite is true. Workers who have experienced a job-to job transition in the last 6 months experience within-job wage growth that is lower by around 1% . A pattern that is consistent acrross all subsamples, eventhough the differences are not statistically significant for workers with at most a high school diploma. This clearly underlines that this alternative explanation is not likely to be the driving force of the empirical patterns we have presented.

In this sub-section we have presented our explanation for the empirical regularities that we see in the data and we have shown that alternative explanations that could generate the same patterns are not likely to be important. In the next section we show that we can reproduce the patterns of the data by using a simple on-the-job search model with shocks to the firm-specific component of wages.

3 Model

3.1 The Environment

The model is in continuous time. Workers live forever and discount the future at rate ρ. They enjoy income and dislike looking for a job. They cannot borrow or save. Workers can be either unemployed or employed. If they are unemployed, their utility function is given by

$$u(b) - e,$$

where b is the unemployment benefit and e is the effort that the worker utilizes in his job search activities. This effort is a control variable and it is optimally chosen by the individual. If the worker is employed, his utility is

$$u(w) - e,$$

where w is the income that he will receive from his employer.

When unemployed, a worker receives wage offers w from the distribution $F(w)$ at a rate $\lambda_u(e)$. The function $\lambda_u(\cdot)$ is assumed to be increasing, concave, and twice differentiable. When employed in a firm w, the worker receives wage offers w' from the same distribution $F(w)$ at a rate $\lambda_e(e)$; he becomes exogenously separated from his employer at a rate δ; and he receives wage shocks at a rate γ such that his new wage is $w+v$, where v comes from $F_v(v)$.

3.2 The Dynamic Problem

The model is described by the following two value functions: U is the value of unemployment and $V(w)$ is the value of being employed in a firm w[3] :

$$\rho U = \max_e \left\{u(b) - e + \lambda_u(e) E \max(V(w) - U, 0)\right\}, \tag{2}$$

$$\begin{aligned} \rho V(w) \quad = \quad & \max_e \{u(w) - e + \gamma E_v \max(V(w+v) - V(w), U - V(w)) + \\ & +\delta(U - V(w)) + \lambda_e(e) E \max\left(V\left(w'\right) - V(w), 0\right)\right\}. \end{aligned} \tag{3}$$

[3]We define the expectation operators as $E(\cdot) = \int (\cdot)\, dF(w)$ and $E_v = \int (\cdot)\, dF_v(v)$.

The first-order conditions with respect to the effort yield:

$$\begin{aligned}\lambda_u'\left(e^U\right) &= \frac{1}{E\max\left(V\left(w\right)-U,0\right)} \to \lambda^u, \\ \lambda_e'\left(e^V\right) &= \frac{1}{E\max\left(V\left(w'\right)-V\left(w\right),0\right)} \to \lambda\left(w\right).\end{aligned}$$

where it can be shown that $\lambda'(w)$ is decreasing in w. Furthermore, the model implies two reservation rules. An unemployed worker will accept a wage offer if it is higher than w^* where $w^* = \arg_w \left(V\left(w\right)=U\right)$. An employed worker will accept a wage offer w' if and only if $w' > w$. Using these results we can re-write the value functions as:

$$\begin{aligned}\rho U &= u\left(b\right)-e+\lambda_u\int_{w^*}\left(V\left(w\right)-U\right)dF\left(w\right), \qquad (4)\\ \rho V\left(w\right) &= u\left(w\right)-e+\gamma\int_{w^*-w}\left(V\left(w+v\right)-V\left(w\right)\right)dF_v\left(v\right)+ \\ &\quad+\left[\delta+\gamma F_v\left(w^*-w\right)\right]\left(U-V\left(w\right)\right)+ \\ &\quad+\lambda_e\left(w\right)\int_w\left(V\left(w'\right)-V\left(w\right)\right)dF\left(w'\right)\cdot\end{aligned}$$

4 Simulation

Given that we do not know how many shocks in a given year are received by employed workers or when they are received, the likelihood function of this model is intractable. Instead we use a simulation-based method. We simulate the data using our model to replicate the NLSY. We select some of the parameters using the NLSY sample that we replicate, and we identify the rest of the parameters using auxiliary models. We estimate the transition probabilities by matching the implied transition probabilities from a multinomial logit with no job change, a job-to-job transition (JJ), and job to unemployment to job (JUJ) transitions. We also use a set of regressions of log wage and log earnings (true and constructed) in changes like the one we use to show the patterns in the data. Because the regressions are in changes, we can skip the estimation of all those parameters that affect only wage level and earnings level.

In the rest of the section, we explain the structure of the simulation as well as how we identify each component of the parameter vector.

4.1 Structure of Simulation

We simulate our data in the following steps. We assume that a worker enters in the sample with a job; i.e., the first observation for each worker is in the period he has his first full-time job.

We then simulate a duration for the following events: new wage, new acceptable offer, and separation. Next, we take the first of the three events and record the relevant random variables: duration and wage of the spell and job number related to the spell (this will allow us to determine job mobility). For the wage, we draw the non-search component and the firm-specific factor. The next period, three events could happen to this worker: 1) experience a wage change within the same employer, 2) become unemployed, or 3) change jobs. The rate at which these three events happen are

$$\gamma\left(1-F_v\left(\varepsilon^*-\varepsilon\right)\right)$$
$$\lambda\left(\varepsilon\right)\left(1-F_\varepsilon\left(\varepsilon\right)\right)$$
$$\delta+\gamma F_v\left(\varepsilon^*-\varepsilon\right)$$

For unemployed workers we do the same, but the job number and the wages are not recorded. If unemployed, only one thing can happen to the worker the next period, and that is to find a job, which happens at rate λ^u.

We stop when the sum of all spells reaches T years.

Once we have T years of data for each worker, we aggregate the spells to interview years to replicate the NLSY79. Then we aggregate the data to calendar years, as in our version of NLSY using also information on interview dates and selecting "usual wages" as the wage rate that occurred most frequently during that period of time.

4.2 Parameter Vector

There are 11 parameters of the model that are needed for the simulation.

We assume that the log of wages is the sum of an individual specific fixed effect (h_i), a time-varying component that is independent of the search process (X_{it}), a firm-specific component (ε_{jt}), and an idiosyncratic transitory random variable (μ):

$$\ln w_{ijt} = h_i + X_{it} + \varepsilon_{jt} + \mu_{it}$$

where variables in X_{it} are year dummies, age, race, and schooling. We assume that these variables, X_{it}, are worker specific and therefore do not affect the parameters of the search process.

All the parameters relative to variables that are assumed to affect wage levels but not wage growth are not estimated. These are the constant, the individual's fixed effect, race, and schooling.

Therefore, we need only the parameters relative to age and age squared. They are the constant and the linear term of the regression in first differences.

$$\beta_1, \beta_2$$

The firm-specific factor follows a normal distribution, and we need the following parameters

$$\varepsilon^*, \sigma_\varepsilon$$

The shock to the firm-specific component is assumed to follow a normal distribution with standard deviation σ_v and mean μ_v.

We also need the unemployment value, b, and the arrival rates for unemployed, λ^u, and employed workers, $\lambda(\varepsilon)$. Finally, we need the exogenous separation rate, δ, and arrival rate of wage shocks, γ.

4.3 Calibration

We use our compared sample in NLSY to find the values of 6 parameters (See Table 7). We set λ^u as the inverse of the average unemployment duration in our sample, which implies that unemployed workers receive 1.76 offers per year. Similarly δ reflects the inverse of average employment duration, and implies that the probability of a match ending for exogenous reasons is 20.34%.

For the coefficients on age and age squared on wage growth, we use information on the first wage after unemployment. In particular, we use the estimates of fixed effect of log wages on age, age square and year dummies. These parameters show an inverse U-shaped returns to experience; returns to experience are positive (5.34%) but at a decreasing reate.

It is reasonable to assume that wages and earnings are measured with error. As can be seen from the data, wages are very volatile and a large fraction of this volatility is transitory. The measurement errors in wages and earnings are assumed to be normal with standard deviation σ_w and σ_e. We follow Keane and Wolpin (1997) and assume that the standard deviation of measurement error in wages and earnings is 9.18% of the variance in observed wages and earnings respectively.

We follow Heckel et al (2008) and assume that the probability of getting a shock to wages is 35% quarterly; this implies that $\gamma = 1.8$ on an annual basis.

Having fixed these 7 parameters, we have 5 parameters to calibrate: the arrival rate for employed workers, the unemployment benefit, the parameters of the firm-specific factor $(\varepsilon^*, \sigma_\varepsilon)$, and the variance of the shock to the firm-specific component, σ_v (we normalize its mean to zero). We use indirect inference to estimate these 5 parameters. In particular, we choose parameters for our simulated data to match the fraction of job-to-job transitions and the coefficients on JJ and JUJ on a set of regressions of log wage and log earnings in changes like the one we use to show the patterns in the data (Table 3).

Calibrated parameters are presented in Table 8. The performance of the model in matching calibration targets is presented in Table 9. The model is able to match the dynamics of both wages and earnings for workers who experienced a job to job transition (relative to those that stayed at the same employer). The variance of the shock to the employer-employee match allows us to match these two targets. The variance of this shock is 4 times the variance of the firm-specific factor. Employed workers receive on average 2.44 offer per year, 0.68 more offers than unemployed workers. Under this baseline calibration, 59% of the observed wage cuts following job to job transitions are due to the deterioration of the firm-specific component faced by workers before they switch employers.

To study how sensible the results are to our assumptions, we recalibrate the model assuming that workers do not receive shocks to the firm-specific component (this would be equivalent to calibrating a standard job ladder model). For this calibration we follow the same calibration strategy as before and we shut down the shock by setting $\sigma_v = 0$. Table 10 adds to Table 9 the coefficients of the two regressions for this modified version of the model. Under this specification all observed wage cuts are due to measurement problems. This translates to workers receiving fewer offers while on the job. However, the adjustment of $\lambda(\varepsilon)$ is not enough to match the disimilar dynamics of earnings and wages. The results show that the standard job ladder model is not able to replicate the average fall in earnings of workers that experience a job-to-job transition relative to those that remained at their employer.

5 Conclusion

The job ladder model has been the workhorse for the literature that studies the relationship between job mobility and wage dynamics. We show that the standard job ladder model cannot reconcile wage dynamics and earnings dynamics across different labor market transitions in the U.S. We explore alternative explanations of that discrepancy through wages and earnings growth regressions across different labor market transitions using NLSY79 and SIPP data. We find that the most convincing hypothesis supported by the data is the existence of shocks to the firm-specific component.

We use two independent measures of workers' compensation to provide a convincing identification strategy for the presence of a job-specific or employer-specific wage shock process. In the first measure, workers are asked about the usual wage they earn with a certain employer. In the second measure, workers are also asked their total amount of labor earnings during the previous year. While the first measure records the wages at a given point in time, the second measure records the sum of all wages from one year.

We calibrate a generalized search model in which workers can receive a shock to their productivity match (as in Nagypal (2005) and JPVR (2006)) using both measures of workers' compensation and data on employment transitions. In our model, job-to-job transitions move workers up the ladder, but they move relative to the last wage at each employer. Because the firm-specific match can receive shocks, wages may increase or decrease over time at each employer. Therefore, for some workers, job-to-job transitions are a way to escape job situations that worsened over time.

The results show that it is important to include shocks to earnings to the standard job ladder model. In our baseline calibration 59% of the observed wage cuts following job to job transitions are due to deterioration of the firm-specific component of wages before workers switch employers. The model that ignores the job-specific or employer-specific wage shock is not able to replicate the different dynamics in wages and earnings of workers that experience a job-to-job transition relative to those that remained at their employers.

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Table 1: Descriptive Statistics

Variables	
Number of Observations	16,430
Average Age	28.32
Average Years of Schooling per individual	12.61
Average Years of Potential Experience	7.96
Percentage of Blacks	11.3%
Average log (Hourly Wage)	2.04
Average log (Hourly Labor Earnings)	1.99
Average log (Hourly Constructed Labor Earnings)	2.03
Percentage of Job to Job Transitions	12.9%
Percentage of Job to Unemployment to Job Transitions	12.1%
Average Duration of Unemployment (weeks)	29.6

Table 2: Income growth by employment transition and education level

	Switched jobs		Stayed in the same job	
	HCE	HE	HCE	HE
All workers	4.82%	−1.35%	3.38%	5.03%
High school dropout	3.37%	−6.07%	2.21%	4.00%
High school graduates	4.64%	−2.32%	2.99%	4.79%
Some college or more	5.76%	2.26%	4.47%	5.83%

Table 3: Earnings and wage growth

Transition	Wages	Earnings	
between t-1 and t		Observed	Constructed
Switch employer (JJ)	0.0421***	-0.0718***	0.0221***
	(0.0135)	(0.0157)	(0.00832)
Job to Unemployment to Job (JUJ)	-0.0265*	-0.0691***	-0.0451***
	(0.0152)	(0.0240)	(0.0117)
Observations	16,473	12,826	16,473
R-squared	0.003	0.005	0.005

Note: All specifications control for experience, education,race, and year dummies. Robust standard errors in parentheses. (***) $p < 0.01$,(**) $p < 0.05$, (*) $p < 0.1$.

Table 4: Earnings and wage growth

	Paid by the year		Paid by the hour	
Transition between t-1 and t↓	HE	HCE	HE	HCE
Switch employer (JJ)	0.0367	0.0169	-0.100***	0.0409***
	(0.0324)	(0.0215)	(0.0268)	(0.0130)
Job to U to Job (JUJ)	-0.0622	0.0162	-0.0231	-0.0421***
	(0.0495)	(0.0373)	(0.0376)	(0.0162)
Observations	2,708	3,693	3,373	4,439
R-squared	0.009	0.003	0.005	0.007

Note: All specifications control for experience, education, race, and year dummies.

Robust standard errors in parentheses. (***) $p < 0.01$,(**) $p < 0.05$, (*) $p < 0.1$.

Table 5: Earnings growth, ignoring one week

Transition between t-1 and t↓	Weekly earnings
Switch employer (JJ)	-0.0301**
	(0.0152)
Job to U to Job (JUJ)	-0.0458*
	(0.0238)
Observations	12,826
R-squared	0.003

Note: All specifications control for experience, education, race, and year dummies.

Robust standard errors in parentheses. (***) $p < 0.01$,(**) $p < 0.05$, (*) $p < 0.1$.

Table 6: Monthly labor earnings growth, future and past transitions

	All workers	Young workers	Workers with at most high school	Workers with at least some college
JJ	0.164***	0.167***	0.136***	0.193***
	(0.005)	(0.005)	(0.007)	(0.007)
JUJ	0.009	0.015	-0.012	0.0461**
	(0.012)	(0.012)	(0.015)	(0.019)
Layoff	-0.077***	-0.071***	-0.067***	-0.087***
	(0.012)	(0.013)	(0.017)	(0.018)
JJ within the next 6 months	-0.011***	-0.012***	-0.014***	-0.010***
	(0.002)	(0.003)	(0.004)	(0.003)
JUJ within the next 6 months	0.017***	0.016**	0.020**	0.009
	(0.006)	(0.006)	(0.008)	(0.010)
Layoff within the next 6 months	0.007	0.006	0.014	-0.006
	(0.006)	(0.007)	(0.009)	(0.010)
JJ within the past 6 months	-0.008***	-0.009***	-0.006	-0.010***
	(0.003)	(0.003)	(0.004)	(0.003)
JUJ within the past 6 months	-0.017***	-0.018***	-0.016**	-0.017*
	(0.006)	(0.006)	(0.008)	(0.010)
Layoff within the past 6 months	-0.011*	-0.012*	-0.019**	-0.001
	(0.006)	(0.007)	(0.009)	(0.009)
Observations	307,074	269,161	135,948	171,126
R-squared	0.004	0.004	0.003	0.005

Robust standard errors in parentheses. (***) $p < 0.01$,(**) $p < 0.05$, (*) $p < 0.1$.

Table 7: Parameter Values

Parameter	Definition	Basis
$\beta_1 = 0.0534$	Return to potential experience	First wage after unemployment (NLSY79)
$\beta_2 = -0.0028$	Quadratic term of return to pot experience	First wage after unemployment (NLSY79)
$\delta = 0.2134$	Prob of exogenous separation	Inverse of employment duration (NLSY79)
$\gamma = 1.8$	Prob of receiving a shock to firm specific factor	Heckel et al (2008)
$\lambda_u = 1.76$	Prob of receiving a job offer while unemployed	Inverse of unemployment duration (NLSY79)
$\sigma_u = 0.1976$	Sd Dev of measurement error in wages	Wolpin (1987) and Hourly wages (NLSY79)
σ_ε	Sd Dev of Firm specific factor	Calibrated to match targets
ε^*	Min value of firm specific factor for acceptable wage offer	Calibrated to match targets
σ_v	Sd Dev of shocks to wages	Calibrated to match targets
λ_e	Prob of receiving a job offer while employed	Calibrated to match targets
b	Unemployment benefit	Calibrated to match targets

Table 8: Matching the calibration targets

Target	Data	Model
Wage growth regression		
coefficient of JJ	0.0421	0.0300
coefficient of (JUJ)	-0.0265	-0.0577
Earnings growth regression		
coefficient of JJ	-0.0718	-0.0708
coefficient of (JUJ)	-0.0691	-0.0651
Fraction of JJ transitions	0.1290	0.1292

Table 9: Calibrated parameters

σ_ε	Sd Dev of Firm specific factor	0.05
ε^*	Min value of firm specific factor for acceptable wage offer	-0.02
σ_v	Sd Dev of shocks to wages	0.10
λ_e	Prob of receiving a job offer while employed	2.44
b	Unemployment benefit	-4.04

Table 10: Matching the calibration targets

Target	Data	Model	Model without shock
Wage growth regression			
coefficient of JJ	0.0421	0.0300	0.0428
coefficient of (JUJ)	-0.0265	-0.0577	-0.0343
Earnings growth regression			
coefficient of JJ	-0.0718	-0.0708	0.0078
coefficient of (JUJ)	-0.0691	-0.0651	-0.0071
Fraction of JJ transitions	0.1290	0.1292	0.1581