ECONOMIC RESEARCH
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WORKING PAPER SERIES

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Working Paper Number	2014-032A
Creation Date	October 2014
Citable Link	https://doi.org/10.20955/wp.2014.032
Suggested Citation	Canon, M.E., Pavan, R., 2014; Wage dynamics and labor market transitions: a reassessment through total income and usual wages., Federal Reserve Bank of St. Louis Working Paper 2014-032. URL https://doi.org/10.20955/wp.2014.032

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

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October 2014

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. The contribution of our paper relies on our novel approach to identifying the presence of the shock to the match specific productivity. The presence of two independent measures of workers' compensation in our dataset of is crucial for our identification strategy. 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.

Keywords: wage dynamics, earnings dynamics, job mobility.

JEL codes: J3, J6

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‡For helpful discussions and insightful comments, we thank Juan Sanchez and seminar participants in the University of Rochester, Federal Reserve Bank of St. Louis, Federal Reserve Bank of Minneapolis, Washington University in St. Louis, and the Central Bank of Chile. We also thank Judy Ahlers for editorial assistance.

1 Introduction

Topel and Ward (1992) initiated an extensive literature in empirical economics documenting the positive impact of job mobility on wages for young workers. Since then, the job ladder model has been the workhorse for explaining the positive correlation between job mobility and wage growth. 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 experience. 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). An extension of the standard job ladder model proposed to ameliorate these failures is the introduction of a shock to the existing employer-employee match. Workers who are hit by a negative shock are more likely to leave their employer.

Our's paper main contribution is its novelty identification strategy for the presence of the shock to the existing employer-employee match. The presence of two independent measures of workers' compensation is crucial to our identification strategy. We use a particular feature of the National Longitudinal Survey of Youth (NLSY79) to uncover the evolution of workers' compensation over time. 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, the first measure can be considered a time-dependent function evaluated at one point, whereas 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 explaining the nature of the wage shock for employed workers. We show that studying only data on *wages* we might confuse w*age cuts* with the impact of measurement error. Some wage movements that appear to be wage cuts might be due to measurement errors. Using a second independent measure of income, albeit different in nature (flow versus stock) helps to distinguish measurement error from true wage cuts.

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 United States. We explore alternative explanations of that discrepancy through wages and earnings growth regressions across different labor market transitions using data from both the NLSY79 and Survey of Income and Program Participation (SIPP). We show that although the wage dynamics are consistent with a job ladder model, the same is not true for the earning dynamics. 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 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. 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; 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 NLSY79. We select some of the parameters using the NLSY79 sample that we replicate, and we identify the remaining parameters using auxiliary models. The results show the importance of including shocks to earnings in 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

In their seminal paper, Topel and Ward (1992) estimated 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 job changes. They initiated an extensive literature documenting the positive impact of job mobility on wages for young workers. 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 explaining 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 wage rate reduction fraction was only 26 percent for workers who remained at their current employer.

An extension of the standard job ladder model proposed to ameliorate these failures is the introduction of a shock to the existing employer-employee match. The underlying rationale for 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 been unable to provide a convincing identification strategy for such shocks.

In virtually all datasets, wages are not continuously observed but are sampled at most only a few times a year. Therefore, changes in observed wages may hide the fact that a worker received a negative shock between observations and decided to leave his employer. That is, the wages a worker receives after changing jobs might be lower than the wage 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

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

(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 the worker's job search activity during the notice period. This reallocation shock allows JPVR 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) propose a search-matching model where they allow 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) also develop a search-matching model with two-sided heterogeneity that incorporates productivity shocks, long-term contracts, on-the-job search, and counter offers. These features imply that a worker might accept a wage cut as a result of wage renegotiation. Productivy shocks are an idiosyncratic shock that arrives at rate δ. When a shock arrives, a new productivity level is drawn from the unconditional distribution (as in Postel-Vinay and Turon, 2010; and JPVR, 2006). The authors use the within-job and between-job variance of wage growth to identify the rate of arrival of productivity shocks (δ).

In summary, all the identifying strategies in job search and search-matching models identify frequency of productivity shocks. Our goal in this paper is to propose a strategy that uses two independent measure of workers' compensation, which although different in nature (flow versus stock) help to distinguish measurement error from true wage dynamics.[2]

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 allowing 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] Identification strategies using employer-employee data have been able to provide a richer identification of those processes (see, for example, Postel-Vinay and Robin, 2002, and Cahuc, Postel-Vinay, and Robin, 2006).

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 nonmilitary men, at least 25 years old, who are not enrolled in school and do not own a business. We do not include the oversample 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 11 % 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 NLSY79 constructed the Work History File, which provides the weekly labor market history of each individual over the entire 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 measure 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 a worker receives in a given year, excluding dual job holders, is simply the sum of all wages received, denoted as

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

where $E\left(t+1\right)$ 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 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

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

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, constructed earnings (CE) is equal to

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

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 easily be 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 these two variables to 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 (HE), and hourly contructed earnings (HCE) for our sample. Average labor earnings in our sample shows 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 displayed by the true earnings. 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 previous 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.[3] 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 NLSY79 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 NLSY79 provides a measure of the worker's *usual* wage at the old job between

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

t and $t+\Delta$ and a measure of the *usual* wage at the new job between $t+\Delta$ and $t+1$.

In the previous section, we showed that labor earnings can be constructed using wage information, given the assumption that wages are relatively stable during a survey year. 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 HE and HCE of male workers between 25 and 65 years of age, conditional on the worker having 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 HE growth is not as strongly positively correlated with job-to-job transition as is HCE growth, a pattern present across 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 HE by an average of 2.6% in years when they switched employers, which is still 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.

2.3.1 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, at both the intensive and extensive margins, 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

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

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 systematic differences exist between these two approaches to calculating the same statistics. In Table 3, we report the coefficients of an ordinary least squares (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 who 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 find that job-to-job transitions are associated with an earnings decline of 7%. As we previously mentioned, this disconnection between the two measures must be explained by the failure of one of our assumptions 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, cautious is needed in interpreting these coefficients given that, for example, we do not include any measure of severance payments in our calculation of constructed earnings.

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 who are paid by the hour and those who 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 who switch employers experienced a 4% higher increase in their constructed earnings relative to those who stayed at the same employer. However, HE for those same workers who switch employers decreased on average 10% more than those workers who did not switch employers. For workers paid by the year, there are no significant differences in earnings and constructed earnings between workers who switched employers and workers who 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 HE we rely on the weekly information provided by the NLSY79. However, if a worker experiences unobserved unpaid working gaps between two consecutive jobs, we could overestimate HCE and underestimate true HE. This sort of non-classical measurement error could replicate the patterns that we observed. We take a conservative strategy to address this concern . To construct true HE 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. Table 5 shows the results which suggest this correction is far from adequate 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 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 worker might not consider the last wage paid by the employer by to be his *usual* wage because he left that employer relatively soon after such a change. This might also explain why so many negative wage changes are observed 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 attemp to (i) find explanations that could compete with our preferred story and (ii) 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 explain both our observation of 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, provided 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 final wage in the old job and the first wage in the new job would be enough to distinguish the two stories apart. Although this is not possible, we can look at an alternative dataset for additional evidence. The SIPP provides monthly labor income as well as hourly wages and hours worked month by month. Unfortunately, SIPP provides these data only for workers paid by the hour. This implies that we observe monthly wages for a worker who changed employers only if both employers paid the worker by the hour. This restriction does not allow the use of SIPP data 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. Nevertheless, it does provide additional evidence to support one of the two alternative hypotheses.

We use the 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). In addition to contemporaneous labor market transitions, we add dummies for future and past labor market transitions. We observe workers in our panel over 48 months. For each period t, we look at a worker's labor market transitions during the previous six months ($t-6$) and the future six months ($t+6$). If the worker switches employers in any of the subsequent six months ($t+6$), the

"JJ within the next 6 months" dummy will take a value of 1. This dummy allows us to identify earnings growth behavior before the switch occurred. Similarly, if the worker switches employers in any of the six previous months ($t-6$), the "JJ within the past 6 months" dummy will take a value of 1. In this case, the dummy identifies how earnings grow during the first 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 earnings estimates with standard errors shown in parentheses. Consistent with our story, workers who will experience a job-to-job transition within the next 6 months (on average) experience a 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 within the past 6 months experience within-job wage growth that is lower by around 1%. This pattern is consistent across all subsamples, even though the differences are not statistically significant for workers with at most a high school diploma. This clearly indicates that this alternative explanation is not likely the driving force of the empirical patterns presented.

In this subsection we have presented our explanation for the empirical regularities seen in the data, and we have shown that alternative explanations that could to generate the same patterns are not likely to be important. In the next section, we show 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 used 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 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:[4]

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

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

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

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

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 $w^* = \arg_w (V(w) = U)$. An employed worker will accept a wage offer w' if and only if $w' > w$. We

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

can use these results rewrite the value functions as follows:

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

4 Simulation

Given that it is unknown how many shocks employed workers receive in a given year 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 NLSY79. We select some of the parameters using the NLSY79 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 similar to the one used to show the patterns in the data. Because the regressions are in changes, we can skip the estimation of all parameters that affect only the wage and earnings levels.

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 the sample with a job—that is, the first observation for each worker is for the period in which 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 allows 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: (i) He experiences a wage change within the same employer, (*ii*) he becomes unemployed, or (*iii*) he changes 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 wages are not recorded. If he is unemployed, only one thing can happen to the worker the next period: he finds 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 NLSY79, also using information on interview dates and selecting *usual* wages as the wage rate that occurred most frequently during that period.

4.2 Parameter Vector

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

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 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, only the parameters relative to age and age squared are needed. 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 the following parameters are needed:

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

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 the arrival rate of wage shocks, γ.

4.3 Calibration

We use our compared sample in NLSY79 to find the values of 6 of the 11 parameters in 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 job 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 the fixed effect of log wages on age, age squared and year dummies. These parameters show inverse U-shaped return to experience; return to experience are positive (5.34%) but at a decreasing rate.

It is reasonable to assume that wages and earnings are measured with error. As the data show, 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, respectively. 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 5 parameters remained to be calibrated: 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 as we did to show the patterns in the data (Table 3).

Calibrated parameters are presented in Table 9. The performance of the model in matching calibration targets is presented in Table 8. 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 who 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 offers 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 8 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 employed. However, the adjustment of $\lambda(\varepsilon)$ is not enough to match the dissimilar dynamics of earnings and wages. The results show that the standard job ladder model cannot to replicate the average decrease in earnings of workers who experience a job-to-job transition relative to those who remain at their employer.

5 Conclusion

The job ladder model has been the workhorse for studies of 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 United States. 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 their usual wage earned 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 for 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 the importance of including 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. The model that ignores the job-specific or employer-specific wage shock cannot replicate the different dynamics in wages and earnings of workers who experience a job-to-job transition relative to those who remained at their employers.

References

[1] Burdett and Mortensen (1998). "Wage Differentials, Employer Size, and Unemployment." International Economic Review, vol. 39(2), 257-73.

[2] Cahuc, P., F. Postel-Vinay, and J.-M. Robin (2006): "Wage Bargaining with On-the-Job Search: Theory and Evidence," Econometrica, 74(2), 323–364.

[3] Eckstein and van den Berg (2007). "Empirical labor search: A survey." Journal of Econometrics, vol 136, Issue 2, 531-564.

[4] Flinn and Heckman (1984). "New methods for analyzing structural models of labor force dynamics." Journal of Econometrics, vol 10, 115-168.

[5] Heckel, T, Le Bihan, H, and Montornès J (2008). "Sticky wages: evidence from quaterly microeconomic data". European Central Bank, Working Paper Series No 893.

[6] Jolivet, Postel-Vinay and Robin (2006). "The Empirical Content of the Job Search Model: Labor Mobility and Wage Dispersion in Europe and the U.S." European Economic Review, vol 50(4), 877-907.

[7] Lise, J, Meghir, Costas, and Robin J (2013). "Mismatch, Sorting and Wage Dynamics". NBER Working Paper No. 18719

[8] Lopes de Melo, R (2007). "The implications of Search Models for Wage Dynamics: an Empirical Assessment." Working paper, University of Chicago.

[9] Lopes de Melo, R. (2009): "Sorting in the Labor Market: Theory and Measurement," Discussion paper, University of Chicago.

[10] Keane, M and Wolpin, K (1997). "The Career Decisions of Young Men". Journal of Political Economy, 105 (3): 473-522.

[11] Nagypal, E (2005). "On the Extent of Job-to-Job Transitions." Working paper, Northwestern University.

[12] Postel-Vinay and Robin (2002). "Wage Dispersion with Worker and Employer Heterogeneity." Econometrica, vol 70(6), 2295-350.

[13] Postel-Vinay and Turon (2010). "On-the-job Search, Productivity Shocks, and the Individual Earnings Process." International Economic Review, vol 51(3), 599-629.

[14] Topel and Ward (1992). "Job Mobility and the Careers of Young Men." The Quarterly Journal of Economics, vol. 107(2), 439-79.

[15] Wolpin (1987). "Estimating a structural job search model: the transition from school to work." Econometrica, vol 55, 801-818.

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