Wage Risk and the Value of Job Mobility in Early Employment Careers

Kai Liu, *University of Cambridge*

This paper shows that job mobility is a valuable channel that employed workers use to mitigate bad labor market shocks. I estimate a model of wage dynamics jointly with a dynamic model of employment and job mobility. The key feature of the model is the specification of wage shocks at the worker-firm-match level, for workers can respond to these shocks by changing jobs. I find that, relative to the variance of individual-level shocks, the variance of match-level shocks is large and the consequent value of job mobility is substantial, particularly for workers whose match-specific wages are low.

I. Introduction

Understanding how much idiosyncratic risk people face and how individuals respond to different types of risks is important for a number of reasons. There is an extensive literature analyzing individual's precautionary behavior under incomplete markets, such as savings and labor supply.[1]

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[1] See, among others, Deaton (1992), Carroll (1992), Gourinchas and Parker (2002; precautionary savings), and Low (2005; precautionary labor supply). See Meghir and Pistaferri (2011) for an excellent review.

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The implications of these models depend critically on the assessment of the levels of wage risk and the persistence of the shocks.

In most papers, changes in properly defined wage residuals represent shocks, and researchers rely on the autocovariance structure of these residuals to identify the magnitude of wage risks that are distinguished by the persistence of the shocks.[2] With a few exceptions discussed below, most of the existing literature does not specify sources of wage shocks. Understanding how individuals respond to different types of risks is important, as government programs (such as unemployment insurance) often insure against specific sources of shocks to income and can have incentive impacts on individual's behavior against risks (Meghir and Pistaferri 2011). In addition, because changes in the wage residuals are observed after individuals have made choices, policy changes that affect individuals' behavior may potentially affect the residual wages and the wage risks identified therein. This makes it hard to evaluate government programs unless we understand how wage dynamics are affected by individual behavior.

This paper aims to advance our understanding of wage risk along two dimensions. First, I distinguish two types of wage shocks, one type occurring at the worker-firm-match level and the other occurring at the individual level, which applies to all firms and matches. The decomposition of wage risk into match-specific and worker-specific wage risk is economically significant because they have very different implications for individuals' behavior and policy. For instance, contrary to shocks at the individual level, negative shocks at the match level do not mean that permanent depreciation of an individual's general productivity will occur, as it may be recovered by the worker through job mobility. Second, by modeling workers' job mobility decisions in response to labor market shocks, I show the value of job mobility as a channel of response to the match-level risk facing employed workers and illustrate how it may be affected by alternative policies. The model is also capable of recovering the true wage risk, defined as the wage risk facing workers prior to their job mobility choices, which may be quite different from the wage risk inferred from observed wages after job mobility.

I build and estimate a wage process jointly with a structural dynamic model of job mobility and employment. The wage process features four independent and linearly additive components: a component that is predicted by personal characteristics, an individual component, a match component, and a measurement error. The match component can be interpreted as job-specific

[2] See, among others, Abowd and Card (1989), Haider (2001), Baker and Solon (2003), Meghir and Pistaferri (2004), Blundell, Pistaferri, and Preston (2008), Moffitt and Gottschalk (2012), Jensen and Shore (2015), and Blundell, Graber, and Mogstad (2015). More recently, Lochner and Shin (2014) provide nonparametric identification results for a model of wage dynamics allowing for changes in unobserved skills.

human capital or an idiosyncratic firm effect on wages.[3] The match component and individual component follow parallel stochastic processes: each evolves from a permanent shock with a drift. Shocks therefore represent permanent deviations from the corresponding growth profile. In the structural model, both unemployed and employed workers search for outside offers with costs. Offer arrival rates depend on search intensity, which is chosen optimally by individuals. Employed workers make job mobility and employment decisions following the wage process. They also face an exogenous layoff risk. The model implies that only the match component is correlated with job mobility choices, which can be used to separately identify the match component from the individual component in the wage residuals. Similar to Topel and Ward (1992), I find strong empirical evidence that workers' mobility decisions are correlated with job-specific wage changes in the past. The strong correlation between lagged within-job wage growth and job mobility is informative of the potentially important role of match-level shocks (see Sec. III for details).

The model is estimated by the method of simulated moments using longitudinal data on young male workers from the 1996 panel of the Survey of Income and Program Participation (SIPP). I find that wage risk at the match level accounts for the majority of the wage risk facing workers. For instance, match-level risk can explain 81.9% and 67.5% of the overall variance of wage growth for low- and high-education men with 8 years of potential experience, respectively. Individual-level productivity risk explains no more than 5% of the overall variance of wage growth. That the majority of wage risk is at the worker-firm level has important implications for job mobility and wages. For instance, it implies that, for certain workers, job mobility can be an important channel to react against negative wage shocks. Match-level wages are also important in terms of explaining overall wage growth and inequality over early careers, particularly for low-education individuals and individuals with few years of potential experience. Finally, given the large fraction of match-level shocks and the relatively high rate of job mobility in early careers, the true wage risk is a few times larger than the implied wage risk ignoring match-level wage shocks.

Counterfactual analysis conducted in this paper further highlights the importance of distinguishing sources of wage shocks and modeling job mobility behavior against match-level shocks. I find that the value of job mobility in reducing the welfare cost of negative match-level shocks is substantial, particularly for workers whose match-specific wages are low. Policies that increase the value of unemployment tend to reduce the value of job mobility. Relative to job mobility, raising unemployment income alone pro-

[3] Empirically, it is infeasible to distinguish pure firm effect from pure worker-firm-match effect without employer-employee matched data. This term is also referred to as match-specific wages or match-level wages throughout the paper.

vides a relatively small reduction in the welfare cost of negative match-level shocks, and this additional value is largely crowded out when job mobility is available to respond to these shocks. Therefore, the value of unemployment benefits against match-level shocks could be overstated without accounting for endogenous job mobility response to shocks. To the best of my knowledge, this is the first paper that studies the welfare value of job mobility as a mechanism for workers to respond to labor market shocks.[4] The value of job mobility in this context builds on the premise that job mobility can be affected by match-specific wage fluctuations via changes in both reservation wages and search intensity. In a seminal paper, Topel and Ward (1992) find evidence that previous job-specific wage growth affects workers' job mobility decisions (holding the current wage and other observed characteristics fixed). However, they find this result "somewhat puzzling in light of our previous evidence that within-job wage growth approximates a random walk" (473). This suggests that one needs to estimate a stochastic wage process jointly with a worker's job mobility choices, which is the direction taken in this paper.

Two closely related papers, Altonji, Smith, and Vidangos (2013) and Low, Meghir, and Pistaferri (2010), make important contributions to the literature by modeling earning dynamics and employment choices jointly. Low, Meghir, and Pistaferri (2010) estimate a wage process incorporating an individual's selection process between jobs and into and out of employment. Their estimates suggest that, once job mobility decisions are controlled for, the variance of permanent shocks is much lower. This suggests that what has been identified as the permanent wage risk from a typical error-component model contains variability due to responses to shocks through job mobility. Altonji, Smith, and Vidangos (2013) construct a rich statistical model of earning dynamics from equations governing wage determination, hours of labor supply, job-to-job transition, and transitions into and out of unemployment. They show that job mobility and unemployment, among other factors, play a key role in determining the variance of earnings over a career.

The current paper contributes to this line of research in a few dimensions. One important difference is that both Altonji, Smith, and Vidangos (2013) and Low, Meghir, and Pistaferri (2010) assume that the worker-firm-match component of the wage does not vary over the duration of the job. Within-job wage changes are assumed independent of a worker's job mobility decision. Therefore, there is no match-specific wage risk except the unem-

[4] Several other important channels individuals use in response to labor market risk have been pointed out in the literature, including Low (2005; labor supply), Kaplan (2012; within family), Blundell and Pistaferri (2003; means-tested program), Gruber (1997; unemployment insurance), Low and Pistaferri (2010; disability insurance), and Dillon (2018), Sanders (2014), and James (2012; occupational choice).

ployment risk. One key feature of the current paper is to model wage dynamics within jobs and workers' selection across jobs and into unemployment. By doing so, it distinguishes wage risk that is particular to a worker-firm match from wage risk applying to all jobs. Similarly to Altonji, Smith, and Vidangos (2013) and Low, Meghir, and Pistaferri (2010), I find that the estimated variance of permanent shocks (from canonical models) is reduced when endogenous mobility is taken into account and match value is held constant within jobs. However, incorporating a dynamic process of match within jobs yields a much higher wage risk facing workers prior to job mobility decisions, mainly from the large estimated match-level risk.

In this paper, the structural model is estimated jointly with the wage process, thereby imposing all of the restrictions from the model on the evolution of the wage process. By contrast, in both Low, Meghir, and Pistaferri (2010) and Altonji, Smith, and Vidangos (2013), identification of the wage process relies on a reduced-form model of endogenous mobility decisions without imposing all of the restrictions implied by a structural model. Although estimating the wage process with selection corrections implied by reduced-form equations may be attractive in many ways, welfare implications of job mobility and related counterfactual analysis are best described by a fully estimated structural model of job mobility. Low, Meghir, and Pistaferri (2010) evaluate the welfare implications of different types of risks by using the preestimated wage process from the reduced-form model to calibrate the remaining structural parameters in a life-cycle model of consumption, labor supply, and job mobility. While the model in the current paper adds to their model in certain dimensions (such as endogenous search intensity and shocks to match quality, which affects job mobility and employment decisions), it does not allow workers to save and ignores certain public insurance programs during unemployment. Since an individual's response to wage risk will depend partly on the availability of either self-insurance (such as savings) or public insurance, the welfare value of job mobility estimated in this paper is likely to be an upper bound.

A few recent papers in the structural job search literature also make important contributions to understanding wage dynamics, including Yamaguchi (2010), Postel-Vinay and Turon (2010), Bagger et al. (2014), and Lise, Meghir, and Robin (2015).[5] These studies use an equilibrium job search model to an-

[5] Postel-Vinay and Turon (2010) focus on how purely transitory productivity shocks are able to transform into persistent wage shocks that are consistent with the covariance structures implied in the wage data. The key mechanisms underlying such transformation are wage renegotiations and on-the-job search. Yamaguchi (2010) estimates a model of on-the-job search with wage bargaining. He empirically explores the effect of outside option values, match quality, and human capital accumulation on the wage growth of young workers. Using employer-employee matched data, Bagger et al. (2014) estimate an equilibrium job search model of worker careers,

alyze the wage dynamics implied by the model, emphasizing the role played by firms and wage determination and providing insights on how productivity shocks are translated to wages. The focus of the current paper is the workers' endogenous decisions (search intensity, job mobility, and employment) that translate the process of "offered" wages into realized wages that are consistent with the structure of the wage data. Relative to the equilibrium search models, the wage process in this paper is relatively more general, and consequently the labor market turnover decisions feature additional heterogeneity and dynamics. For instance, in this paper the wage process features heterogeneous worker and match productivity, each of which evolves stochastically with its own shocks and drifts; the structural model also allows for endogenous search intensity and quit to unemployment following wage shocks.[6] More importantly, besides using the model to explain wage dynamics, the current paper adds to the literature by quantifying the value of job mobility in mitigating negative match-level shocks and showing how this value may be affected by policy environment. By being agnostic to firms' wage policies, one main limitation of the paper is that the job creation and the offered wage distribution is assumed exogenous and invariant to policy change, which may generate bias to the counterfactual analysis.

The rest of the paper proceeds as follows. Section II describes the wage process and the dynamic model of job mobility and employment. Section III presents the data and descriptive evidence that motivates this study. Section IV discusses the estimation and identification strategy. Section V presents estimation results of the main structural model and contrasts them with estimates from alternative models of wage processes. Section VI discusses implications of the structural model for sources of wage risk and inequality, and it presents the welfare value of job mobility against match-level shocks and discusses how it might be affected using counterfactual analysis. Section VII concludes. Additional materials and results are provided in the appendix (available online).

II. The Model

I build a dynamic model of job search in which an individual makes choices about search intensity, job mobility, and employment. The assump-

allowing for human capital accumulation, employer heterogeneity, and individual-level shocks. One important addition of their paper is the ability to estimate firm heterogeneity using employer-employee matched data. Lise, Meghir, and Robin (2015) develop an equilibrium model of wage determination and employment that allows for the possibility of assortative matching between workers and jobs.

[6] For instance, Postel-Vinay and Turon (2010) ignore the impact of human capital accumulation, and Bagger et al. (2014) allow only for individual-level shocks but not match-level shocks. In both papers, transitions from employment to unemployment are assumed exogenous.

tions of the model are as follows. An individual i maximizes the expected present value of utility over a finite horizon, subject to a wage process specified below. At the beginning of each period (t), the individual (either unemployed or employed) chooses the search intensity, which then determines the rates of offer arrival. If the individual is employed, he makes the following discrete choice: move to a different job if an offer arrives, become unemployed, or stay with the current job. The worker's acceptance decision of job offers depends on the relative quality of the current match and the offered match. If the individual is unemployed, he chooses either to become employed (if an offer arrives) or to remain unemployed. This section begins by presenting the wage process. Details on the choice structure and decision rules are discussed in Section II.B.

A. The Wage Process

The life-cycle wage process for the individual i employed by firm j in period t is

$$\ln \tilde{w}_{ijt} = \ln w_{ijt} + v_{it}, \tag{1}$$

$$\ln w_{ijt} = \beta_0 + a_{ijt} + u_{it}, \tag{2}$$

$$a_{ijt+1} = \begin{cases} a^{l}_{ijt+1} & \text{if no job change between } t \text{ and } t+1, \\ a^{o}_{ij't+1} & \text{if job change between } t \text{ and } t+1, \end{cases}$$

$$a^{l}_{ijt+1} = a_{ijt} + c + \eta_{ijt+1}, \quad a^{o}_{ij't+1} \sim N(0, \sigma^2_{a_0}), \tag{3}$$

$$u_{it+1} = u_{it} + \delta + \zeta_{it+1}. \tag{4}$$

Assume that

$$\zeta_{it} \sim N(0, \sigma^2_{\zeta}), \quad \eta_{ijt} \sim N(0, \sigma^2_{\eta}), \tag{5}$$

$$E(v_{it}) = 0, \quad \mathrm{var}(v_{it}) = \sigma^2_{v}, \tag{6}$$

$$u_{i0} \sim N(0, \sigma^2_{u_0}), \tag{7}$$

with orthogonality between these error terms. The term $\ln \tilde{w}_{ijt}$ is the observed real log hourly wage for worker i employed by firm j in period t, and v_{it} is a measurement error (more on the latter below). For an employed worker, the log wage residual (after taking out the constant term β_0) is decomposed into two components: an individual component, u_{it}, and a match component, a_{ijt}, between firm j and worker i. Equations (3) and (4) describe the potential (or "offered") wage in period $t+1$, conditional on the actual wage in period t (discussed below). All parameters of the wage process are specific to the completed education level of the individual.

The individual component (u_{it}) measures the worker's general productivity regardless of his employer. It evolves over the life cycle from an independent and identically distributed (i.i.d.) permanent random shock ζ_{it} and a growth factor δ. The term $\sigma^2_{u_0}$ measures the initial heterogeneity of general productivity. The individual component corresponds to the concept of permanent wage in the literature, which is usually thought of as representing return to skill or flow from human capital. The term δ captures return to work experience, perhaps through differential learning ability to general skills or human capital investment.[7]

Parallel to the individual component and prior to selection between jobs, the match component follows a random walk process with a growth factor. Let a^l_{ijt+1} be the latent match at $t + 1$ prior to job mobility (l represents latent). It evolves from a growth factor (drift), c, and a permanent shock, η_{ijt}, which is identically and independently distributed across firms, workers, and time. One interpretation of the match component is that it is an idiosyncratic firm effect that is complementary to individual productivity. From the perspective of human capital theory, the match component can also be regarded as job-specific human capital. The growth factor (c) can be thought of capturing return to tenure (or firm-specific human capital). The shock to the match component then represents a worker-firm-specific permanent deviation from the mean growth rate.[8] This would happen, for example, when in a particular year the firm does not provide enough training to enhance the worker's firm-specific skills (negative η_{ijt}) or it adopts a new technology that is complementary to the worker's productivity (positive η_{ijt}). In general, it consists of both a pure match-specific shock and a pure firm-specific shock, although without firm-level data, distinguishing between these is not feasible. More broadly, the match component can be interpreted as any factor that affects the worker's productivity with the current firm but not after he

[7] One plausible mechanism that links the growth in the individual-level wage component to wage growth is to assume that wages are offered on the basis of piece-rate contracts, as in Burdett, Carrillo-Tudela, and Coles (2011) and Bagger et al. (2014). In this case, human capital accumulation increases output (via learning-by-doing), and log wage is a linear combination of the individual human capital, worker-firm match, and contractual piece rate.

[8] One interesting area to explore is to allow the growth factor to be worker-firm specific, which can generate some very interesting wage dynamics at job changes because job mobility depends on the combination of wages and their growth rate (Burdett and Coles 2010). In the data, we are unable to observe the entire wage-tenure profile for a large number of jobs (in the SIPP data, the number of wage observations per person is a maximum of 12 periods, or 4 years). Therefore, given the censoring problem, it is difficult to estimate the effects of heterogeneous wage-tenure profile. Note that if there is a lot of heterogeneity in the returns to tenure, then part of the match-level shocks defined in this paper may be heterogeneity and known at the time of job mobility choice. In this case, the estimated match-level risk is likely to be an upper bound.

leaves for other firms.[9] The growth factor and permanent shocks to the match component are accumulating only over the current job tenure and will "vanish" after a job destruction. Match- and individual-specific log wage shocks are assumed to follow normal distributions with zero means and variances σ^2_η and σ^2_ς, respectively.[10]

A job offer with match-specific wage a^o (o stands for offer) is a random draw from a stationary offer distribution. I assume that it follows a normal distribution with mean zero and variance $\sigma^2_{a_0}$. Because of the growth profile in the individual component of wage (due to δ), the mean offered wages would be shifting with the worker's labor market experience. Offered matches are assumed uncorrelated with the worker's individual wage component, which implies that there is no assortative matching in the labor market.

When worker i receives an offer from firm j' at time t, prior to making a job mobility decision the worker is perfectly informed of his general productivity (u_{it}), match-specific productivity (a^l_{ijt}) if he chooses to stay, and the value of the offer ($a^o_{ij't}$).[11] At any time, workers have perfect information about their current match value, the expectation of future match values, and the distribution of the match component in the labor market, but information on other job locations and their associated match value must be obtained through search. I assume that none of the shocks to u_{it} and a_{ijt} are anticipated by the worker, so they represent wage uncertainty.[12]

Measurement errors are identically and independently distributed across individuals and over time. Measurement errors may also capture some transitory wage shocks at either the worker-firm-match level or the person level, although they must affect wages *after* the mobility decision is made in each period.[13] In the canonical decomposition of shocks into transitory and per-

[9] Note that the newly accepted match would be positively correlated to the old match because of selection (that workers move only toward jobs that are more productive than their current job).

[10] The distribution assumptions are stronger than the standard permanent-transitory decomposition in the literature, but they are necessary in order to correct for selection bias due to endogenous employment and mobility (see Sec. VI for details).

[11] I abstract from uncertainty about worker productivity and any private and public learning. For instance, Harris and Holmstrom (1982) and Farber and Gibbons (1996) explore the implications for wage dynamics of the assumptions that employers learn about worker productivity over time and information is public; Waldman (1984) and Greenwald (1986) analyze models in which the incumbent employer has an information advantage. Farber and Gibbons's result that employer learning induces a martingale component into the wage process (holding worker productivity fixed) provides a structural interpretation of wage dynamics.

[12] This excludes the possibility that parts of these random shocks may be known to workers in advance. See Cunha, Heckman, and Navarro (2005).

[13] In other words, they are unrelated to job mobility and employment decisions. It is potentially interesting to allow transitory shocks to affect job mobility and employment, although this would increase the computational burden substantially. Ad-

manent components, transitory shocks may well be important because of unemployment spells or temporary job spells.[14] In the structural model, these sources of transitory shocks are modeled explicitly through employment and job mobility decisions. For instance, for the match-level wage process, the distinction between permanent and transitory is less important; permanent match shocks, albeit permanent from the view of workers, can be transitory ex post if job-to-job transitions occur quickly (see Sec. VI.A for some evidence).

B. The Model of Job Mobility and Employment

1. Utility Function

The baseline utility function is specified as follows:

$$U_{ijt} = P_{it} \ln w_{ijt} + (1 - P_{it}) \ln b. \tag{8}$$

The individual's utility depends on the log wage ($\ln(w_{ijt})$) if he is working ($P_{it} = 1$). The log wage (without measurement errors) evolves subject to the stochastic process specified above. While unemployed, the worker receives a utility flow ($\ln b$), where b includes unemployment benefits.

2. Intertemporal Optimization Problem

The intertemporal optimization problem can be written in recursive form using value functions. All individuals begin their lives in the unemployment state and have a finite horizon denoted by T. Since the decision period is discrete, additional restrictions are placed on the timing of the events. In particular, it is assumed that the individual is only able to receive a job offer conditional on the current job not being displaced. Search intensity is chosen to maximize expected utility at the beginning of period t, prior to the realizations of wage shocks in period t.[15] After search intensity is chosen, wage shocks are first realized, and the workers make job mobility decisions based on the new wages. When the individual is displaced, he has to remain unemployed for at least one period.

ditionally, we need to assume that workers have perfect information to distinguish transitory shocks from permanent ones.

[14] For instance, Gottschalk and Moffitt (1994) provide some descriptive evidence that job mobility could be the main contributor to transitory wage shocks.

[15] This timing restriction is made to reduce the computational burden for solving the value function because we do not need to integrate out the optimal search intensity when evaluating the continuation value function (see below). It is worth keeping in mind that shocks are permanent, and therefore the search intensity in period $t + 1$ will depend on the shock in period t.

Let $\boldsymbol{S}_i$ denote the set of state variables summarizing the individual's permanent characteristics (such as initial heterogeneity in the wage equation). The value of nonemployment for the individual in period t is defined by

$$\begin{aligned} V_t^n(u_{it}, \boldsymbol{S}_i) = {} & \ln b \\ & + \Gamma \max_{\lambda_{it+1}^n} \{ \lambda_{it+1}^n E \max [V_{t+1}^n(u_{it}, \boldsymbol{S}_i), V_{t+1}^e(a_{ijt+1}, u_{it}, \boldsymbol{S}_i)] \\ & + ((1 - \lambda_{it+1}^n) V_{t+1}^n(u_{it}, \boldsymbol{S}_i) - \phi^n(\lambda_{it+1}^n) \}, \end{aligned} \quad (9)$$

where Γ is the discount factor and λ_{it+1}^n is the optimal search intensity for the unemployed individual in period $t + 1$, normalized to equal the job-finding rate.[16] In periods of nonemployment, the individual wage component is held constant (i.e., $u_{it} = u_{it+1}$).[17] The term $V_{t+1}^e(a_{ijt+1}, u_{it}, \boldsymbol{S}_i)$ is the value of employment if the worker is offered a job with match productivity of a_{ijt+1}, and $\phi^n(\lambda_{it}^n)$ defines search costs incurred during unemployment given the offer arrival rate λ_{it}^n. It is assumed that the function $\phi^n(\cdot)$ is strictly increasing and convex with $\phi^n(0) = 0$. The job offer is acceptable to the individual provided that $V_{t+1}^e(a_{ijt+1}, u_{it}, \boldsymbol{S}_i)$ is larger than $V_{t+1}^n(u_{it}, \boldsymbol{S}_i)$.

The value function of employment with the firm j in period t is given by

$$\begin{aligned} V_t^e(a_{ijt}, u_{it}, \boldsymbol{S}_i) = {} & \ln(w_{ijt}) \\ & + \Gamma \max_{\lambda_{it+1}^e} \{ \lambda_{it+1}^e (1 - \rho) E \max [V_{t+1}^e(a_{ijt+1}, u_{it+1}, \boldsymbol{S}_i), \\ & \qquad V_{t+1}^e(a_{ij't+1}, u_{it+1}, \boldsymbol{S}_i), V_{t+1}^n(u_{it+1}, \boldsymbol{S}_i)] \\ & + (1 - \lambda_{it+1}^e)(1 - \rho) E \max [V_{t+1}^e(a_{ijt+1}, u_{it+1}, \boldsymbol{S}_i), V_{t+1}^n(u_{it+1}, \boldsymbol{S}_i)] \\ & + \rho E [V_{t+1}^n(u_{it+1}, \boldsymbol{S}_i)] - \phi^e(\lambda_{it+1}^e) \}, \end{aligned} \quad (10)$$

where λ_{it+1}^e is the optimal job-finding rate when the individual is employed and ρ is the exogenous layoff probability in each period. The term $\phi^e(\lambda_{it}^e)$ defines search costs incurred during employment given the offer arrival rate λ_{it}^e. As for the ϕ^n function, I assume that $\phi^e(\cdot)$ is strictly increasing and convex and that $\phi^e(0) = 0$. Note that the marginal costs of search potentially differ by employment status, reflecting differences in technology or oppor-

[16] Note that λ_{it+1}^n (and λ_{it+1}^e in the value function of employment below) is not inside the expectation operator because it is chosen prior to the realization of wage shocks in period $t + 1$.

[17] This assumes away any exogenous depreciation of skills following job loss. Without skill depreciation, unemployment may lead to wages on reentry being lower either because of selection into unemployment (in terms of unobservable characteristics u_{it}) or because the new job will on average have a lower match value.

tunity costs between on-the-job search and search during unemployment. When the individual accepts an external offer, his match component will be the match value offered by the new firm ($a_{ij't+1}$). The dynamics of state variables a_{ijt} and u_{it} follow the wage process specified previously. For instance, if the individual continues with the same job in the next period, his wage paid by the current employer then adjusts to a new level to absorb the returns to tenure and experience, permanent shocks to the individual, and match components of wages. The worker may also choose to quit to unemployment following a large negative shock to either a_{ijt} or u_{it}.

Among employed workers, the optimal search intensity, λ_{it}^e, is determined by the first-order condition[18]

$$\frac{\partial\phi^e(\lambda_{it}^e)}{\partial\lambda_{it}^e} = (1-\rho)E\max\left[V_t^e(a_{ijt}, u_{it}, S_i), V_t^e(a_{ij't}, u_{it}, S_i), V_t^n(u_{it}, S_i)\right] - (1-\rho)E\max\left[V_t^e(a_{ijt}, u_{it}, S_i), V_t^n(u_{it}, S_i)\right], \tag{11}$$

where the marginal cost of search effort is equated with the marginal benefit of search effort given by the difference between the optimized values of current job and employment when an external offer arises. Because the marginal benefit of search declines with match-level wages and the assumption of increasing marginal cost of effort (holding all else constant), the optimal search intensity declines with match-level wages while employed.

For unemployed individuals, the optimal search intensity, λ_{it}^n, is determined by the first-order condition

$$\frac{\partial\phi^n(\lambda_{it}^n)}{\partial\lambda_{it}^n} = E\max\left[V_t^n(u_{it}, S_i), V_t^e(a_{ijt}, u_{it}, S_i)\right] - V_t^n(u_{it}, S_i), \tag{12}$$

where the marginal benefit of search effort is given by the difference between the optimized values of employment and unemployment. The incentive for unemployment search is large for individuals with high u_{it} because the expected market wage offered relative to unemployment income is increasing in u_{it}.[19] An increase in unemployment benefits (b) reduces the marginal benefit from search, thereby reducing the incentive to search for a job when unemployed. This is the moral hazard effect of unemployment benefits in this model.

[18] Search intensity is normalized to be equal to job offer arrival rates. This normalization is necessary for estimation of the model given that search intensity is not directly observed in the data.

[19] Formally, Mortensen (1986) shows that the optimal search effort increases with the mean of the wage offer distribution.

3. *Employment and Mobility Decisions*

The employment decision can be characterized by a threshold reservation value where the worker is employed if the offered match value is larger than the threshold. The reservation match, $g_t(u_{it}, S_i)$, is defined implicitly by

$$V_t^n(u_{it}, S_i) = V_t^e(g_t(u_{it}, S_i), u_{it}, S_i),$$

where the reservation match for employment depends on the individual permanent component and unobserved type of the individual. It is straightforward to show that $g_t(u_{it}, S_i)$ is decreasing in u_{it}.[20] Therefore, it is expected that an unemployed individual with a high individual-level wage component has a shorter spell of unemployment. This condition also implies that employed workers whose individual-level wages are high have a small probability of quitting to unemployment following a negative match-level shock.

A job mobility decision can be characterized by a threshold reservation value where the worker chooses to move if the offered match is larger than the threshold. For a worker currently employed by firm j, the reservation match, $h_t(a_{ijt})$, is defined implicitly by

$$V_t^e\left(a_{ijt}, u_{it}, S_i\right) = V_t^e\left(h_t\left(a_{ijt}\right), u_{it}, S_i\right).$$

For a worker of type S_i and general productivity u_{it}, the worker chooses to move only if there is an offer such that $a_{ij't}^o > h_t(a_{ijt})$. In a standard model of search on the job with utility linear in the wage and an exogenous wage offer distribution, an employed worker simply accepts any wage that is higher than his current wage (which is the reservation wage). The new reservation wage after job mobility is defined by the wage at the new job (e.g., Burdett 1978). In the current model, because the match-level shocks η_{ijt} are i.i.d. across jobs and over time, it simply shifts permanent income, and the worker does not give anything up by accepting a job with a higher match. Therefore, given that the worker maximizes the present discounted value of log wage, the implied reservation match for job mobility is simply given by setting $h_t(a_{ijt}) = a_{ijt}$.

4. *Implications for Wage Risk*

There are two implications arising from the model of job mobility. First, modeling job mobility decisions is important to identify the true wage risk. As an example, suppose the log wage consists of only the match-specific component subject to permanent shocks. Figure 1 demonstrates two possible wage dynamics for a given worker. Prior to time t, the wage is a_0. At the beginning of period t, he suffers a permanent negative match-specific shock

[20] Both the values of unemployment and employment are monotonically increasing in u_{it}, and, for a 1-unit change in u_{it}, the value of employment increases more than the value of unemployment.

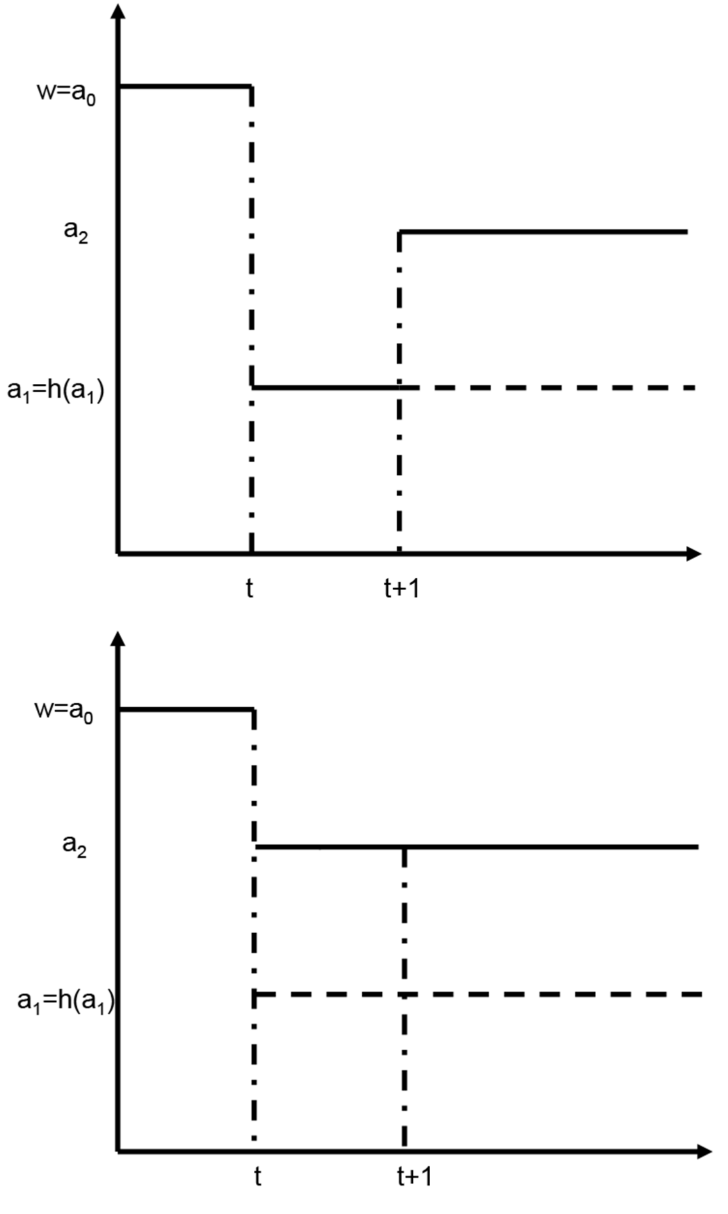

FIG. 1.—Match-specific wages and job mobility.

η, and his new wage is $a_1 = a_0 - \eta$. The permanent wage drop considered here stems from a pure idiosyncratic firm effect and does not mean a depreciation of general individual productivity. In the absence of job mobility, his wage is expected to remain at a_1 for the rest of his working life. Now, suppose a job offer valued a^o arrives at $t + 1$ (top panel of fig. 1). If the new offer is greater than his reservation match $h(a_1)$, he would switch to the new job and earn a wage rate at $a_2 = a^o$. In this case, the wage increase from a_1 to a_2 results from an endogenous job mobility decision rather than the wage shock, a point first emphasized by Low, Meghir, and Pistaferri (2010). Moreover, by changing jobs the worker manages to turn the initial permanent wage shock (η) into one that is effectively partly transitory and partly permanent. Only for a worker who remains at a_1 for a long time is the initial shock correctly identified. The bottom panel of figure 1 depicts a second match dynamic in a similar setting. The only difference is that the worker is able to locate a better job within period t. If the worker takes the job, the observed wage rate in period t becomes a_2, which underestimates the magnitude of true wage shocks. The variance of permanent match-level shocks, σ_η^2, measures wage risk prior to job mobility. The observed average wage per period alone mitigates the initial wage risk facing workers, as it is combined with the worker's response to latent shocks.

The ex post (observed) persistence of the shocks and the extent of the latent wage shocks should depend on how quickly a worker could improve his match by changing jobs. Since the probability of job changes is inversely related to the quality of the contemporaneous match, the model implies that match-specific shocks would appear more (less) persistent for workers of higher (lower) match quality. Therefore, the contribution from permanent shocks on the variance of observed wage changes should be larger for workers of higher match quality. I provide some evidence for this claim in Section VI.A of this paper.

The second insight from the model is that, following a negative match shock, the worker's reservation match becomes lower than the reservation match without the shock. There is now a set of wage offers that are acceptable after the match-level shock that would not have been acceptable without the match-level shock. On top of that, the optimal search intensity also increases as the marginal benefit of searching for outside offers becomes greater. This is how job mobility arises as a channel of ex post response to wage risk. The value of job mobility depends on how the match-level shock affects the worker's job mobility decision, holding the reservation wage fixed at each period. In Section VI.B, I formally define and quantify job mobility as a means of responding to shocks in the labor market.[21] This discussion also highlights the economic importance of modeling the dynamics of the match-specific wage a_j and the person-specific wage u separately. If match quality a_j is con-

[21] This can also be thought as the insurance value of job mobility. Note that the welfare value of job mobility considered here is not the same as shutting down all job mobility. See Sec. VI.B for further discussions.

stant within jobs, then job mobility would not be a useful channel to counteract wage shocks.

III. Empirical Evidence

A. Data and Summary Statistics

The data set I exploit is the 1996 panel of SIPP. It is a 4-year panel comprising 12 interviews (waves). Each wave collects comprehensive information on demographics, labor market activities, and types and amounts of income for each member of the household over the 4-month reference period. There are two main advantages of using SIPP. One is that it has a short recall period, making it an ideal data set to study short-term employment dynamics that are very common among young workers.[22] The other advantage is that SIPP contains a unique job identification for every job an employed worker had through the sample period. It records job-specific wages and hours at each interview date (every 4 months), allowing researchers to obtain the precise wage changes at the time when job transitions take place. These features make it an attractive data set to study short-term job mobility and wage dynamics.

The original SIPP 1996 panel has 3,897,177 person-month observations.[23] I exclude women, full-time students, the self-employed, the disabled, those completing fewer than nine interviews, and those who are recalled by a previous employer after a separation. I trim the population whose real wage falls into the top and bottom 1% of the real wage distribution by wave. I focus on the primary job, which is defined as the job generating the most earnings in a wave. Although SIPP has monthly information on job changes and earnings, the time unit in the analysis of this paper is 4 months (a wave). This avoids the seam bias if we were using monthly variables. Real monthly earnings and the wage are derived by deflating the reported monthly earnings and wage by the monthly US consumer price index for all urban consumers. The reported hourly wage rate is used whenever the worker is paid by the hour. For these workers, the real wage per wave is the mean of monthly real wages over the 4 months. For workers who are not paid by the hour, their real wages are obtained by dividing real earnings by reported hours of labor supply per wave.[24] Job change is identified from a change in job ID between waves. If an indi-

[22] In the selected sample, if a worker is observed to change jobs in a given calendar year, 19% of them would experience multiple job changes within the same calendar year. This means that job mobility observations at an annual frequency understate the extent of job-to-job transitions by about one-fifth.

[23] Note that, due to attrition, not all individuals complete 12 interviews.

[24] For each month, respondents report hours of work per week and how many weeks they worked. Monthly labor supply is calculated as hours per week × (weeks worked/weeks in month) × 4.33.

vidual is unemployed through the wave, no job ID would be assigned.[25] In the first wave of SIPP, respondents are asked the starting date of their present job. I use this information to construct correct job tenure for workers with elapsed job duration when they are first sampled.

I construct two separate panels, one consisting of low-education individuals (those with a high school education) and the other including high-education individuals (those with a college education). Each panel contains individuals aged between 23 and 35 who are observed for eight consecutive waves in the sample.[26] For this group of individuals, job mobility is most frequent and is the most important avenue for wage growth in early careers (Topel and Ward 1992). The final samples consist of 938 men in the high-education sample and 755 men in the low-education sample.

Summary statistics are provided in table 1. Table 2 reports the distribution of the total number of observed job changes in the sample. The initial life-cycle period refers to the periods of potential experience observed in the first sample period. Overall, nearly 45% of the workers switch jobs at least once in the 4-year sample period. The extent of job-to-job transitions decreases monotonically with the potential experience of the individual. For instance, among the most experienced, only 30% of the individuals made at least one job change within the sample period. In contrast, the majority of the individuals who recently entered the labor market made at least one job change by the end of the sample period.

B. Wage Growth and Job Mobility: Descriptive Evidence

In this section, I present a set of descriptive evidence addressing the following questions: First, what is the pattern of within-job wage growth and, in particular, how common are real wage cuts? Second, what is the empirical relation between within-job wage growth and subsequent job mobility? Are

[25] Fujita and Moscarini (2017) document a substantial amount of recall unemployment in the SIPP data (in which a worker is laid off temporally and then hired back by the same firm). It is not possible to separate out recall unemployment in the SIPP panel used in this paper because job IDs are reset by default after an entire wave (1 quarter) of unemployment. Nevertheless, the overall rate of unemployment (recall and non-recall unemployment combined) for the sample of young male workers under study is low. The option of recall unemployment is perhaps more significant in equilibrium models because it directly affects firms' incentive to post vacancies (in Fujita and Moscarini [2017], posting a vacancy is costly, whereas recalling a previous worker is costless). From the view of individual workers, regardless of whether there is a recall, unemployment represents the same underlying phenomenon, that of workers' marginal product being lower than their reservation wage.

[26] In the SIPP data, the maximum duration that an individual appears in the panel is 4 years. We know that many 18–22-year-olds with a high school education would be attending college. Given that the panel is not long enough to observe the highest completed level of education for these individuals, the age range (23–35) is imposed so that people can have completed a college education. In addition, the sample excludes individuals who are full-time students in any wave in the SIPP panel.

Table 1
Summary Statistics, Survey of Income and Program Participation 1996

Variable	Mean	Standard Deviation
Demographics:		
Age	27.40	2.46
White	.72	.45
Some college or more	.55	.50
Metropolitan	.83	.38
Own a house	.49	.50
Married	.54	.50
Labor market variables:		
Wages	11.62	5.35
Hours of work per week	42.11	11.32
Proportion of job-job transition	.10	.30
Elapsed job duration in the first observation period	5.45	5.74
Total number of observations	13,544	

NOTE.—Wages are deflated using the monthly consumer price index for all urban consumers (CPI = 1 in 1996:1) and averaged over a 4-month period (per wave).

workers who experience within-job wage cuts more likely to change jobs? The empirical evidence presented in this section provides useful benchmarks to evaluate the assumptions and implications of the model.

Figure 2 presents the distribution of within- and between-job wage growth. The top panels show the real wage growth calculated as the change in log real wages every 4 months.[27] Two features of the picture are clear. First, between-job wage growth has larger variation than within-job wage growth. Second, both within-job and between-job real wage cuts are very common. Around 45% of job-to-job transitions end up with wage cuts, and about half of within-job wage growths are negative. The majority of the within-job wage cuts are small in magnitude. For instance, the median within-job real wage cut is merely 1.3% per period. There remains, however, a substantial portion of within-job wage growth showing significant drops. Of the within-job real wage cuts, 25% include wage declines of 12% or more between waves. Wage cuts between jobs are much greater in magnitude: the median between-job wage decline is close to 20%. The measurement error may be an important contributor, which is accounted for in the wage process and discussed later. Part of the real wage change could also be due to the stickiness of wages that are not immediately keeping up with the rising cost of living. The bottom panels of figure 2 show the distribution of nominal wage growth between and within jobs. Nominal wage stickiness implies less than 1 percentage point of decline in real wage growth on average, which is very small relative to the extent of wage cuts observed in the data. For instance, the mean quarterly wage growth is 2.17% if real wage is used and 2.84% if nominal wage is used.[28]

[27] Throughout this section, "wage" refers to the real wage unless noted otherwise.

[28] The maximum of quarterly increase in the cost of living leads to a 1.53% decline in real wages. Note that a change in the cost of living will affect both outside

Table 2
Total Number of Job Changes, by Potential Experience

	Number of Job Changes (%)				
Quartile of Initial Life-Cycle Period	0	1	2	3	≥4
<25th (1–4)	45.0	31.7	13.7	5.1	4.4
25th–50th (7–10)	54.9	24.0	14.4	4.9	1.9
50th–75th (13–16)	59.2	25.1	11.8	2.9	1.0
>75th (19–22)	69.2	20.2	8.2	2.4	.0
Total	56.4	25.6	12.2	3.9	1.95

To understand the empirical relation between wages and a worker's subsequent mobility choice, I estimate the following regression using individuals who are employed for at least three consecutive periods:

$$M_{ijt+1} = \alpha_1 \Delta \ln w_{ijt} + x_{it}'\alpha_2 + \gamma_{ij} + \epsilon_{ijt}, \tag{13}$$

where M_{ijt+1} is an indicator variable that is equal to 1 if an individual i employed by firm j in period t moves to a new job in period $t + 1$ (and 0 if the individual does not switch jobs), $\Delta \ln w_{ijt}$ is the within-job wage growth in period t, and the vector x_{it} includes a quadratic in worker's age and year dummies. Worker-job match fixed effects are included to control for any time-invariant unobservables associated with a worker-job match. For instance, γ_{ij} may capture the effect of match-specific permanent wages or permanent wage growth on job mobility. Parameter α_1 is the estimated effect of lagged within-job wage changes on job mobility, holding all of the other covariates constant. If match-level shocks affect future job mobility, as implied by our model, the estimated α_1 should be negative because a worker whose within-job wage growth is low should be more likely to move to another job in the following period. If within-job wage changes are completely due to measurement errors or individual-level productivity shocks, there should be zero correlation between worker's job mobility choices and within-job wage change.

Columns 1–3 in table 3 report the estimates using a linear probability model. In column 1, equation (13) is estimated without the match fixed effects.[29] Columns 2 and 3 build on the specification in column 1 by adding individual fixed effects and individual job match fixed effects, respectively.

offers and incumbent wages, and therefore it will not explain the large between-job wage cuts relative to within-job wage cuts.

[29] In addition to the variables included in the vector x_{it}, in cols. 1 and 2 I also control for the average wage paid by firm j to worker i within the job spell that is observed in the sample period. I do not control for the wage level in the immediate period prior to wage change ($\ln w_{ijt-1}$) in this regression. With transitory shocks, wages are mean reverting, so a low lagged wage ($\ln w_{ijt-1}$; which is due to a negative transitory shock) is more likely to associate with a high wage growth in period t. This would generate a spurious negative relationship between wage growth and job mobility.

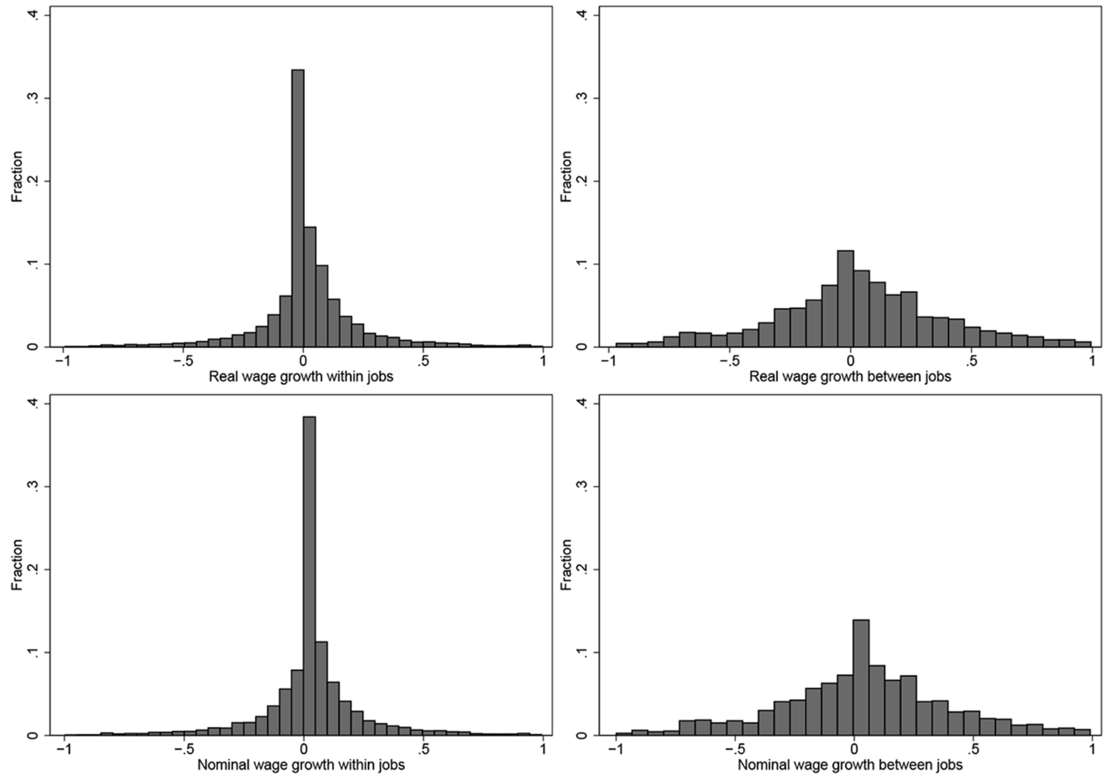

FIG. 2.—Distributions of within- and between-job log wage changes. The top two panels show the distribution of real log wage growth between waves within (*left*) and between (*right*) jobs. The means (standard deviations) are 0.018 (0.24) and 0.052 (0.45), respectively. The bottom two panels show the distribution of nominal log wage growth between waves within (*left*) and between (*right*) jobs. The means (standard deviations) are 0.024 (0.24) and 0.059 (0.45), respectively.

Table 3
Job Mobility and Wage Changes

	(1)	(2)	(3)	(4)
Within-job wage growth	−.034**	−.035**	−.028**	−.983**
	(.013)	(.014)	(.011)	(.443)
Within-job average wage	−.082***	−.717***		
	(.009)	(.090)		
Fixed effects included	No	Individual	Match	Match
Model	OLS	FE	FE	FE-logit
Observations	8,638	8,638	8,638	1,743

NOTE.—Within-job wage growth is measured in period t. The dependent variable is a job change indicator in period $t + 1$ (equal to 1 if a job change occurs). All regressions control for year dummies and a quadratic in age. Standard errors (in parentheses) are clustered by person. See Sec. III for details. FE = fixed effects; FE-logit = fixed effects logistic regression; OLS = ordinary least squares.
** $p < .05$.
*** $p < .001$.

Because the mean rate of job mobility is low, as a robustness check of the linear probability model I also perform the analysis using a fixed effects logistic regression (where the dependent variable in eq. [13] becomes a logistic function of $P(M_{ijt} = 1)$). Column 4 reports the estimates from the fixed effects logit model that include the match fixed effects. For the fixed effects logit models, I report the results in coefficients, or log odds ratios, which are interpreted as the difference in the log of odds of the outcome associated with a unit change in the covariate. The standard errors are clustered at the individual level across all specifications.

I find that within-job wage changes are negatively correlated with future job mobility (col. 1). For instance, a 10% decline in the current wage increases the probability of a job change in the next period by 0.34 percentage points (col. 1). The negative relationship between wage growth and mobility is similar after allowing for individual fixed effects or match fixed effects (cols. 2, 3) and nonlinearity in the regression (col. 4). The fixed effects logit estimate from column 4 suggests that a 10% increase in within-job wage growth decreases the log odds of job mobility by 0.098 times.[30]

The negative coefficient on within-job wage growth suggests that, holding all else equal (including permanent wage, mean job-specific wage growth, worker's age, and tenure), workers who experience small within-job wage growth are more likely to change jobs in the following period. The evidence presented above is informative of the potentially important role of match-level shocks. Note that, because part of the reported wage change is measurement error, the estimated effect of within-job wage growth is likely to be biased toward zero, and the true empirical relation between wage growth and job mobility would be stronger. One of the main tasks of estimating the struc-

[30] The sample size of the fixed effects logit regression reflects the fact that identification of the coefficients is from job spells that include at least one job change.

tural model is to identify the within-job wage variations that are due to measurement errors, match-level shocks, and individual-level shocks, accounting for endogenous job mobility and employment.

IV. Identification and Estimation Strategy

For each education group, the structural model of job mobility is estimated jointly with the wage process. Following Lentz (2009), the search costs are assumed to be exponential functions in offer arrival rate: $\phi^e(\lambda) = K_e\lambda^\gamma$ and $\phi^n(\lambda) = K_n\lambda^\gamma$, where $\gamma > 1$ and K_e and K_n are the search costs required to receive an offer with certainty (i.e., $\lambda = 1$) during employment and unemployment, respectively.[31] The discount factor Γ is not estimated and held fixed at 0.97.[32] In general, the flow utility of unemployment cannot be separately identified from the cost of unemployment search (Eckstein and Van den Berg 2007). The flow utility of unemployment is fixed at the value of log unemployment benefit, where the unemployment benefit is equal to 40% of the average wage in the sample (by education group).[33] The set of parameters to be estimated includes the wage equation parameters (β_0, c, δ, σ^2_{u0}, σ^2_{u0}, σ^2_η, σ^2_ς, σ^2_v) and the parameters that determine the rates of offer arrival and job destruction (K_e, K_n, γ, ρ).

A. Identification

In standard error-component models of wage dynamics, the variances of permanent and transitory shocks are identified via autocovariances (Meghir and Pistaferri 2011). In this paper, identification of all of the structure based on the same standard moments is not feasible when there is endogenous job mobility and employment decisions. For instance, autocovariances of wage changes conditional on remaining in the same job and autocovariances of wage changes conditional on changing jobs would depend not only on the wage process but also on the rest of the parameters of the structural model. Given that the wage shocks in the paper affect employment and mobility decisions, the estimates of the variances of wage shocks, the worker, and the match heterogeneity are biased if selection issues are ignored.

The arguments for model identification are given below. The dynamic model of job mobility can be formulated as a Roy model:

[31] These parametric restrictions ensure that the search cost function is increasing and convex.

[32] The annualized discount factor is $0.97^3 = 0.91$. The value of the discount factor falls within the range of values estimated from finite-horizon dynamic discrete choice models (Keane and Wolpin 1997; Ferrall 2012). I also numerically evaluate the sensitivity of the estimates to alternative discount factors. The slope of the objective function is small around small changes to the discount factor.

[33] Shimer (2005) and Hornstein, Krusell, and Violante (2011) set the unemployment benefit equal to 41% of the average wage, which is equal to the average unemployment insurance replacement rates in the United States.

$$\ln w_{ijt} = \beta_0 + a^l_{ijt} + u_{it} + v_{it},$$
$$\ln w_{ij't} = \beta_0 + a^o_{ij't} + u_{it} + v_{it},$$

where, as previously defined, $\ln w_{ijt}$ is the log wage for an individual i employed by current employer j in period t and $\ln w_{ij't}$ is the offered log wage from firm j'. The offer acceptance rule is simply based on the difference between the offered and the current match values:

$$J^*_{it} = a^o_{ij't} - a^l_{ijt}, \tag{14}$$

$$J_{\mathrm{it}} = \begin{cases} 1 & \text{if } J^*_{\mathrm{it}} > 0, \\ 0 & \text{elsewhere.} \end{cases} \tag{15}$$

When $J_{it} = 0$, $\ln w_{ijt}$ is observed; when $J_{it} = 1$, $\ln w_{ij't}$ is observed. Given the distributional assumptions of the error terms laid out in Section II, we know that a^l_{ijt} is normally distributed conditional on a_{ijt-1} (since η_{ijt} is normally distributed), with mean $a_{ijt-1} + c$ and variance σ^2_η, and $a^o_{ij't}$ is drawn from an independent normal distribution with mean zero and variance $\sigma^2_{a_0}$.[34] These distributional assumptions are sufficient to identify the Roy model (Heckman and Honore 1990). Conditional on the match- and individual-level wages at the beginning of period t and search costs functions, the following moment conditions using data from period t identify the parameters: $P(J_{it} = 1)$, $E(\ln w_{ijt}|J_{it} = 0)$, $E(\ln w_{ij't}|J_{it} = 1)$, $\mathrm{var}(\ln w_{ijt}|J_{it} = 0)$, and $\mathrm{var}(\ln w_{ij't}|J_{it} = 1)$. This gives us five equations in five unknowns $\sigma^2_\xi + \sigma^2_v$, σ^2_η, $\sigma^2_{a_0}$, c, and $\beta_0 + \delta$. This identification argument can be applied successively until the first period, when the distribution of match- and individual-level wages can be derived analytically given the distributional assumptions.

The panel structure of the data facilitates the identification of the model. Moments based on the autocovariances of wages are used to separately identify the variance of individual-level permanent shocks (σ^2_ξ) and the variance of measurement errors (σ^2_v). Covariances of wage changes and job mobility help to identify the return to tenure separately from return to experience. For example, a high return to tenure have differential impacts on within-job wage changes ($E(\Delta \ln w_{ijt}|M_{it} = 0)$) than between-job wage changes ($E(\Delta \ln w_{ijt}|M_{it} = 1)$), whereas return to experience (δ) implies a parallel shift on wage growth regardless of mobility. The labor market friction parameters can be identified using information from wages and transition rates between labor market states (Flinn and Heckman 1982). For instance, cost of on-the-job search (λ^e) can be identified directly from the rates of transitions between jobs. In general, neither λ^e nor λ^n affects the reservation wage for job mobility, but both will affect

[34] Due to the lognormal distributional assumption, the offered wage distribution can be recovered from the truncated distribution of observed wages (which satisfies the identification condition of Flinn and Heckman [1982]).

the reservation wage for employment. Intuitively, if the rate of employment is low, a relatively untruncated distribution of observed wages would imply a high cost of unemployment search relative to on-the-job search, while a heavily truncated distribution would imply a high individual wage component.

B. Estimation Strategy

The model is estimated by the method of simulated moments. Each decision period in the model corresponds to one wave (4 months) in the data. In each iteration in the parameter space, computation of the simulated moments consists of nested loops. In the outer loop, the value functions in the dynamic programming problem are computed backward. In the inner loop, the moments are simulated conditional on the value functions. The presence of match and individual heterogeneity increases the state space. Section A of the appendix describes the solution method to the value function in detail. The method uses Monte Carlo integration and an interpolation method to approximate the value function. The standard errors are computed using the formula described in section B of the appendix.

For each individual in each sample period, we observe job mobility, employment choices, and log wages if the individual is employed. The empirical moments include the means of job mobility, employment, transition from employment into unemployment, and log wages in each sample period and the covariances of job mobility and log wage between any two sample periods. Since SIPP is a short panel, it is typical that some workers have left-censored life-cycle histories when they are observed in the first wave. For these workers, their first observed wages are endogenous, which leads to an initial condition problem (Heckman 1981). The initial condition problem is solved by simulating the model starting from the beginning of the life cycle and evaluating the moments conditional on each individual's first observed life-cycle period τ_i.[35] The mean of elapsed job tenure when a worker is first observed in the sample is added to the set of moments to match.[36] Details of the estimation procedure are discussed in section B of the appendix.

V. Estimation Results

Table 4 reports the estimated parameters of the structural model, separately for low-education and high-education men. Relative to individual-level productivity risk, I find that wage risk at the worker-firm-match level is the primary risk facing employed workers. For instance, among low-education men, the variance of match-level shock (σ_η^2) is 0.005, whereas the

[35] Twenty simulations per individual are conducted. The simulations prior to period τ_i are discarded so that the distribution of τ_i in the simulated sample matches the distribution in the real data.

[36] Recall from Sec. III.A that SIPP contains information on the starting date of a worker's present job when he is first sampled. This information is used to construct the elapsed job tenure at the first interview date.

Table 4
Estimated Model Parameters

	Low Education (1)	High Education (2)
Labor market shocks:		
$\sigma^2_\eta \times 10$	.052	.039
	(.008)	(.007)
$\sigma^2_\zeta \times 10$	.001	.002
	(.007)	(.010)
σ^2_v	.029	.053
	(.002)	(.003)
ρ	.020	.008
	(.000)	(.000)
Mean offered wage:		
c	.002	−.004
	(.000)	(.001)
δ	.011	.024
	(.000)	(.001)
β_0	1.918	2.019
	(.016)	(.022)
Heterogeneity:		
$\sigma^2_{a_0}$	.010	.013
	(.001)	(.003)
$\sigma^2_{u_0}$	.053	.058
	(.005)	(.013)
Search cost:		
K_e	1.214	2.443
	(.224)	(.599)
K_n	2.307	1.837
	(.134)	(.122)
γ	3.715	3.653
	(.225)	(.243)

NOTE.—Standard errors are in parentheses. σ^2_η, σ^2_ζ, and σ^2_v are, respectively, the variances of match- and person-level shocks and measurement errors. c and δ are the return to tenure and return to experience, respectively. $\sigma^2_{a_0}$ is the heterogeneity in the offered match values. $\sigma^2_{u_0}$ is the heterogeneity in the person component of wages at the start of work life. K_e, K_n, and γ are parameters relating to the search costs. ρ is the layoff probability. β_0 is the constant term in the offered log wage equation.

variance of the person-level wage shocks is 50 times smaller and insignificant from zero ($\sigma^2_\zeta = 0.0001$).[37] The relative magnitude of individual- versus match-level shocks is further highlighted in terms of their contributions to overall wage variance in Section VI.A.

Relative to the match- and individual-level permanent shocks, the variance of measurement errors is indeed quite large. Consistent with findings from Gottschalk (2005) and Abowd and Stinson (2011), I find that a substan-

[37] The relative contribution of match-level risk and individual-level risk to the overall variance of wage growth depends on the extent of job mobility. In Sec. VI.A, I evaluate the relative importance of different types of risks in explaining the overall variance of wage growth.

tial quarter-to-quarter variation in wages is due to measurement errors.[38] Note that, even though the variance of measurement errors is large in quarterly data, its contribution to the variance of annual wage is relatively small compared with persistent shocks. When quarterly wages are aggregated to annual wage, the variance of quarterly permanent shocks will be "amplified" more than the variance of quarterly measurement errors.[39]

The estimated returns to tenure (c) is 0.2% per period among low-education men. Among high-education men, the estimated return to tenure is slightly negative (at −0.4% per period). The small estimates of return to tenure are in line with existing estimates that are able to account for selection from job mobility and employment.[40] Relative to the return to tenure estimate, the estimated return to experience is positive and large. The return to experience is relatively higher among the high educated than the low educated (2.4% vs. 1.1% per period). Relative to the return to tenure, match-level shocks can generate large changes in match quality. For instance, for the low-education group, a 1 standard deviation match-level shock is equivalent to 7.2% of the match-level wages, whereas the mean return to tenure is only 0.2% per period. Because workers are able to preserve good match shocks and move away from bad match shocks by job mobility, match-level wage shocks and job mobility alone can generate sufficient positive wage growth over time (see Section VI.A for additional discussion).

The estimated initial heterogeneity of the individual wage component is larger than the match offer heterogeneity. This gap is particularly large among low-education individuals, which has important implications for the sources of wage inequality (to be discussed in the following section). Moreover, it also suggests that the heterogeneity of individual productivity, on top of match heterogeneity, is essential for the model to match both the extent of labor market transitions and wage dispersions.[41] Among low-education men, the

[38] As previously discussed in Sec. II.A, in this paper transitory shocks are interpreted as measurement errors. In the estimation sample, the measurement error in wages may come from two sources: from reported wages for those who are hourly paid and from reported earnings and/or hours for salary-paid workers.

[39] As an illustration, in sec. C of the appendix I show that the permanent-transitory variance ratio in annual data can be six times as high as the ratio defined using quarterly data. The approximation is based on the canonical wage process and Taylor approximation.

[40] For instance, Altonji and Williams (2005) report that their preferred estimate of return to tenure for the United States is about 1% per annum. Note that this literature typically assumes that any shock to within-job wages is transitory and does not relate to turnover behavior. The negative return to tenure among the highly educated coincides with Nagypal (2005), who shows that a decreasing value of match quality over the job tenure is necessary to explain the high rate of job turnover in her data.

[41] Bils, Chang, and Kim (2009) and Hornstein, Krusell, and Violante (2011) show that match heterogeneity alone is insufficient to produce both realistic wage dispersion and unemployment fluctuations at the same time.

estimated marginal cost of unemployment search is large relative to the marginal cost of on-the-job search. This relationship is reversed among the high-education men, where the marginal cost of on-the-job search is larger than that of unemployment search. Holding the marginal benefit of search constant, the offer arrival rate among the high-education (low-education) group tends to be higher (lower) during unemployment than employment.

Figures 3 and 4 report the fit of the model to the sample of low-education and high-education men, respectively.[42] The simulated outcomes exhibit a reasonably good fit to the data. The simulations capture essential features of the data, including the average wage, job mobility, and employment, as well as the variance and autocovariance of wage and mobility. Although the model predicts employment rate closely, it tends to overpredict the transition rate from employment to unemployment. Among low-education men, the model also tends to underpredict the rate of job mobility.

Figure 5 plots the actual and predicted distributions of within- and between-job wage growth of workers. The predicted wage growth does not include any measurement errors. Note that the conditional wage distributions are not among the set of directly targeted moments, and therefore they provide additional evidence of the explanatory power of the model.[43] Overall, the model is able to predict the essential features of the wage distribution. For instance, the model correctly predicts that the distribution of within-job wage growth has much less dispersion than the distribution of between-job wage growth. Except for between-job wage growth among the high educated, the peaks of the densities are predicted reasonably well. However, the model underpredicts the fraction of job changes with negative wage growth. Job mobility with wage cuts has been difficult to reconcile in the job-search literature because, with a stationary wage policy, the worker chooses to switch jobs only if a job offering a higher wage exists.[44] Although the model is successful in predicting some between-job wage cuts (e.g., those due to a cut in the person component of wage or a negative latent match-level shock), the measurement error is essential to explain large wage cuts between jobs.

[42] To evaluate the fitness of the model, I simulate 20 careers for each worker in the sample. For each worker, I then keep 8 periods within each career path according to the individual's first observed life-cycle period τ_i.

[43] The actual distributions are based on the same data used to produce the top panels of fig. 2, except that I have disaggregated the sample by education groups for comparisons with the model predictions.

[44] Postel-Vinay and Robin (2002) and Dey and Flinn (2005) rationalize between-job wage cuts through an on-the-job search with wage renegotiation between worker and current employer responding to outside offers. Hedonic models provide another explanation (e.g., Liu 2016). Many structural estimations of search model (e.g., Wolpin 1992) assume that observed wages contain measurement errors in order to produce a positive likelihood of a wage cut.

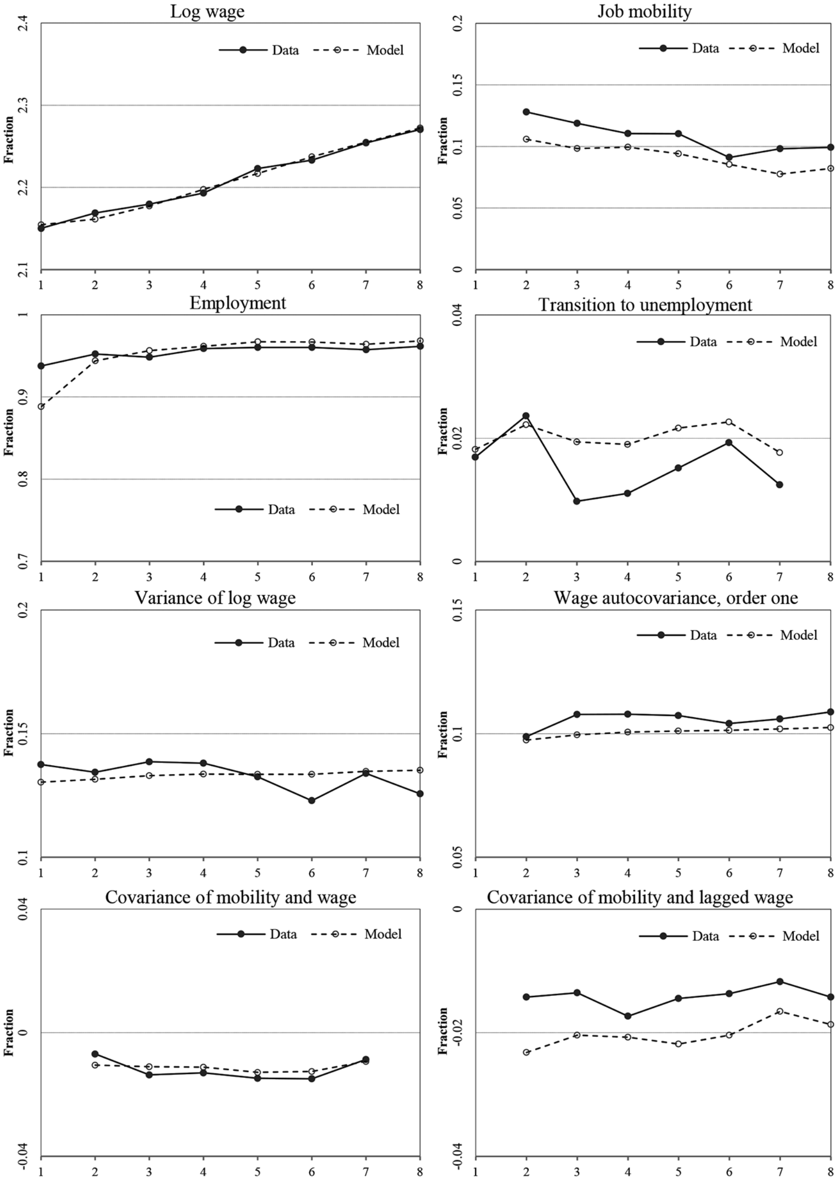

FIG. 3.—Model fit by period: low-education men.

A. Evidence from Alternative Wage Processes

1. Constant Match Quality within Jobs

What happens if shocks to the worker-firm match are ignored? This corresponds to the assumption made in Low, Meghir, and Pistaferri (2010) and Altonji, Smith, and Vidangos (2013), where the worker's mobility choice is

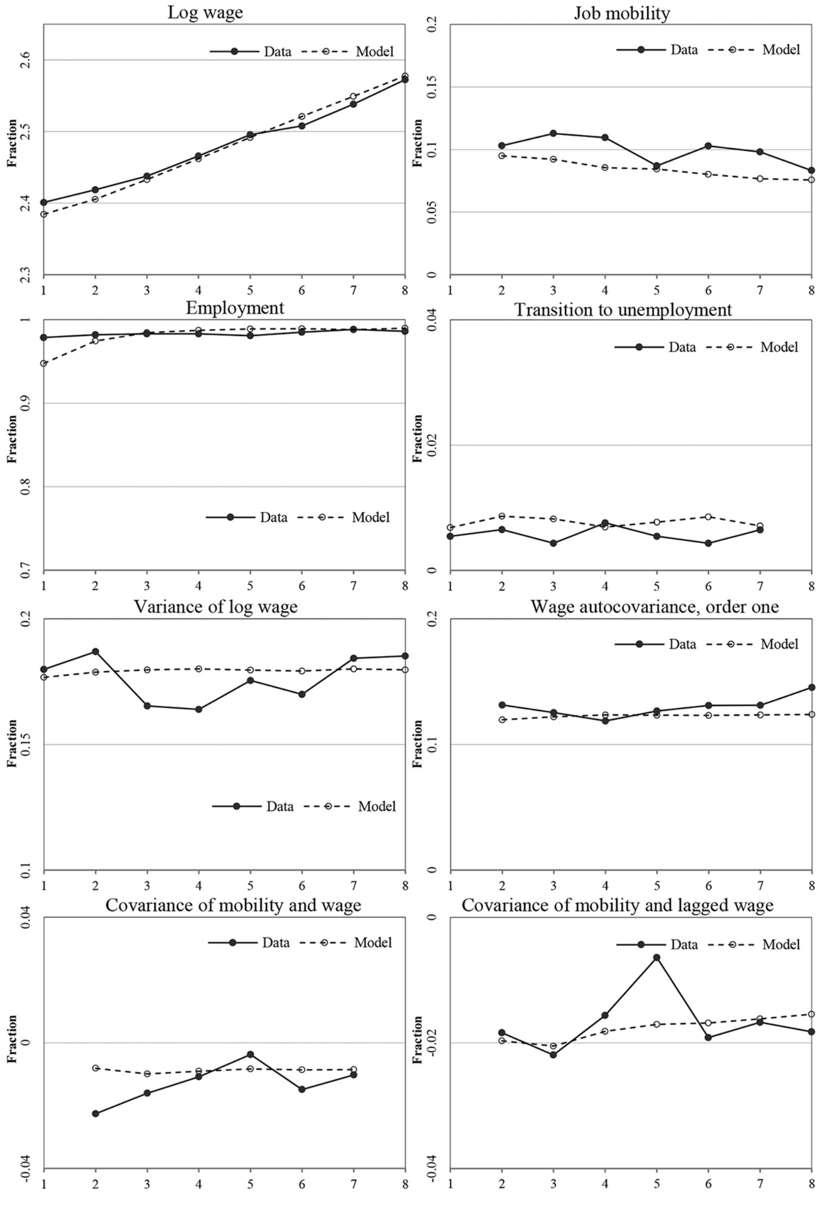

FIG. 4.—Model fit by period: high-education men.

based solely on the value of the initial match.[45] Columns 1 and 3 of table 5 present the estimated parameters when the match values are held constant

[45] Section D of the appendix describes this alternative wage processes. The model is estimated using the same set of moments as described in Sec. IV.

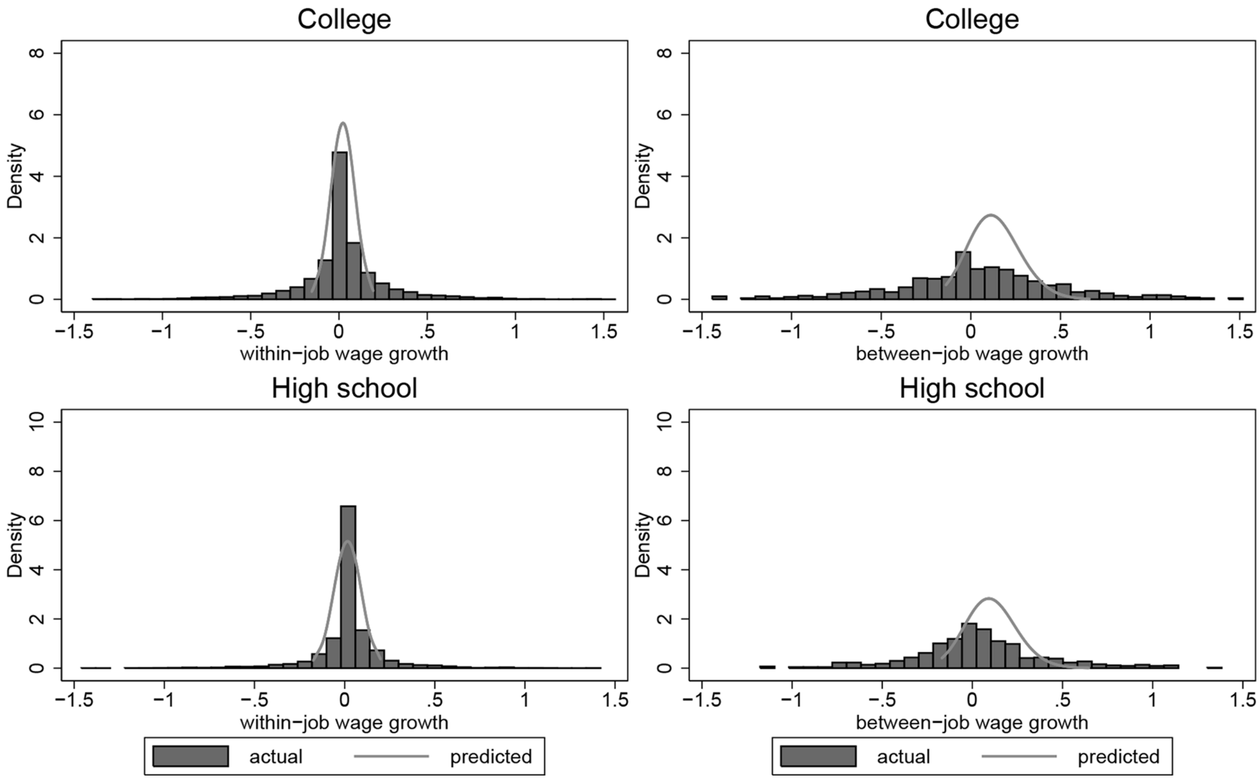

FIG. 5.—Actual and predicted within- and between-job log wage changes.

Table 5
Estimated Model Parameters: Alternative Wage Processes

	Low Education		High Education	
	Constant Match (1)	Exogenous Wage (2)	Constant Match (3)	Exogenous Wage (4)
Labor market shocks:				
$\sigma_\xi^2 \times 10$	.010	.016	.022	.028
	(.007)	(.008)	(.005)	(.010)
σ_v^2	.028	.036	.050	.053
	(.002)	(.002)	(.002)	(.003)
ρ	.012		.013	
	(.000)		(.000)	
Mean offered wage:				
δ	.007	.017	.020	.024
	(.001)	(.001)	(.001)	(.001)
β_0	1.891	1.973	2.070	2.118
	(.013)	(.025)	(.021)	(.026)
Heterogeneity:				
$\sigma_{a_0}^2$	.047		.019	
	(.008)		(.002)	
$\sigma_{u_0}^2$	.063	.062	.065	.057
	(.011)	(.011)	(.005)	(.016)
Search cost:				
K_e	1.408		2.532	
	(.323)		(.487)	
K_n	2.598		1.416	
	(.172)		(.099)	
γ	3.740		3.948	
	(.148)		(.301)	

NOTE.—Standard errors are in parentheses. σ_ξ^2 and σ_v^2 are, respectively, the variances of person-level shocks and measurement errors. c and δ are the return to tenure and return to experience, respectively. $\sigma_{a_0}^2$ is the heterogeneity in the offered match values. $\sigma_{u_0}^2$ is the heterogeneity in the person-component of wages at the start of work life. K_e, K_n, and γ are parameters relating to the search costs. ρ is the layoff probability. β_0 is the constant term in the offered log wage equation.

within jobs for low- and high-education men, respectively. When match-level shocks are ignored, there is a large increase in the estimated variance of individual-level permanent shocks. For instance, among high-education men the variance of individual-level shocks increases tenfold (from 0.0002 to 0.002).[46] A large proportion of wage fluctuations that is specific to a worker-firm match has been identified as permanent shocks that persist across all jobs. In addition to the differences in the estimated individual-level productivity risk, the alternative model also has different implications in terms of the overall wage risk. In the main model, the "true" wage risk is the sum of the variance of the person- and match-level shocks. Under the alternative wage

[46] Note that this estimated variance of individual-level wage shock is not directly comparable to Low, Meghir, and Pistaferri (2010), who assume that the permanent shock occurs each quarter with a probability of 0.25.

process, individual-level productivity risk is the only source of wage risk. A comparison between the two models suggests that the true wage risk is a few times larger than the wage risk implied from this alternative model. For instance, among low-education men the true wage risk is 0.0053 (0.0052 + 0.0001), and the individual productivity risk implied by the alternative wage process is 0.001.

Figures A1 and A2 (figs. A1–A7 are available online) show the fitness of the alternative model against the targeted moments of low-education and high-education men, respectively. Relative to the benchmark model, the alternative model fits the data less well in a few dimensions, although the alternative model also provides a reasonable overall fit to data. For instance, the alternative model fits less well for the covariance moments between job mobility and wage. For the low-education sample, the alternative model overpredicts the rate of employment. For the high-education sample, the alternative model tends to underpredict job mobility and overpredict the transition rate from employment to unemployment.

The alternative model fails to capture two important features of the data that are not among the targeted moments used in estimation. Figure A3 plots the actual and predicted distributions of within- and between-job wage growth of workers from the alternative wage process (without measurement errors). Compared with the predicted distribution from the benchmark model (fig. 5), the alternative model underpredicts the dispersion of within-job wage growth and between-job wage cuts. For instance, among low-education men the benchmark model implies that 14.3% of job-job transitions are associated with a wage cut, whereas the fraction predicted by the constant match quality model is 7%. In the constant match quality model, wage cuts can be rationalized only by a negative shock to individual productivity. The benchmark model can account for additional wage cuts due to negative latent match-level shocks that affect job mobility but are not reflected in the premobility wages. Table A1 (available online) reports the data and model predictions for the (Pearson) correlation coefficients between current within-job wage growth and job mobility in the immediate period. In the data, the correlation coefficients are negative. This pattern is captured by the model including match-level shocks (and measurement errors) but not by the alternative model with constant match quality. When match quality is constant within job spells, within-job wage growth is due to measurement errors and/or individual productivity shocks, neither of which affects job mobility decisions.

2. *Exogenous Wage*

In columns 2 and 4 of table 5, I estimate a canonical wage process that has been frequently used to estimate wage uncertainty in the labor economics and macroeconomics literature. In this model, wages are exogenous; there is no match-specific wage component and no selection into or out of employment and over jobs.[47] Relative to the estimated permanent individual productivity risk allowing for endogenous job mobility and employment, the variance of permanent shocks is larger (but still smaller than the true wage risk defined above). For instance, among low-education men the canonical model implies that the variance of permanent shocks is 0.0016, whereas the alternative model accounting for endogenous job mobility implies that the variance of permanent shocks is 0.001. These results are qualitatively similar to findings of Low, Meghir, and Pistaferri (2010), who show that more than half of the identified permanent wage uncertainty stems from the worker's endogenous job mobility choice.

Figures A4 and A5 show the fitness of the exogenous wage model against the targeted moments of low-education and high-education men, respectively. Overall, the parsimonious model assuming exogenous wage provides a reasonable fit to the variance of autocovariance of observed wages in the data. Relative to the benchmark model, the main feature of the data that the exogenous wage model fails to capture is that the variance of log wages is relatively flat over time in the data. Given that the permanent wage component follows a random walk, the implied variance of log wages is strongly increasing over time. Figure A6 plots the actual and predicted distributions of within- and between-job wage growth of workers from the exogenous wage process (without measurement error). Because job mobility is not part of the model, the exogenous wage process fails to capture an essential feature of the wage distribution—that the distribution of between-job wage growth has large dispersion relative to the distribution of within-job wage growth.

VI. Implications of the Model

A. Wage Growth, Inequality, and Wage Risk in Early Careers

Using the estimated parameters in the model, I simulate 20 paths from the beginning of the life cycle for each individual in the sample. I use the simulated career histories to address the following three questions. First, what are the relative contributions from the match- and individual-level wages to overall wage growth and inequality over time? Second, what is the relative importance of different types of risks on the variance of (residual) wage growth that is typically regarded as wage risk? Third, how persistent are the (realized) match-level shocks after job mobility choices are made?

[47] Section D of the appendix describes this alternative wage processes. This wage process resembles the wage process in Moffitt and Gottschalk (2012) except that the transitory shocks are assumed to be i.i.d. and interpreted as measurement errors for better comparison with the benchmark model. Because job mobility and employment decision are ignored, the model is estimated using the following moments (which are a subset of moments used in estimating the full model): the variances/covariances of wages and mean wages.

To address the first question, I decompose the mean and the variance of simulated population wages over the first 30 periods (10 years) of the life cycle. Wages are defined as wage residuals, abstracting from the permanent offered wage (β_0) and any measurement errors. The top panels of figure 6 examine the age profile of mean wages separately for low- and high-education men. The growth of the individual component ($E(u_{it})$) is due to the positive return to work experience, which is larger among the high educated than the low educated. Among low-education men, match-level wage growth is larger than individual-level wage growth in the first few years in the labor market. After 10 years in the labor market, match-level wage and individual-level wage are equally important in explaining wage growth for the low-education group. For the high-education men, individual-level wage (and therefore return to experience) is the main driving force for overall wage growth for most of the early career. Given the small estimates of return to tenure, the growth in the match component ($E(a_{ijt})$) is due to job mobility

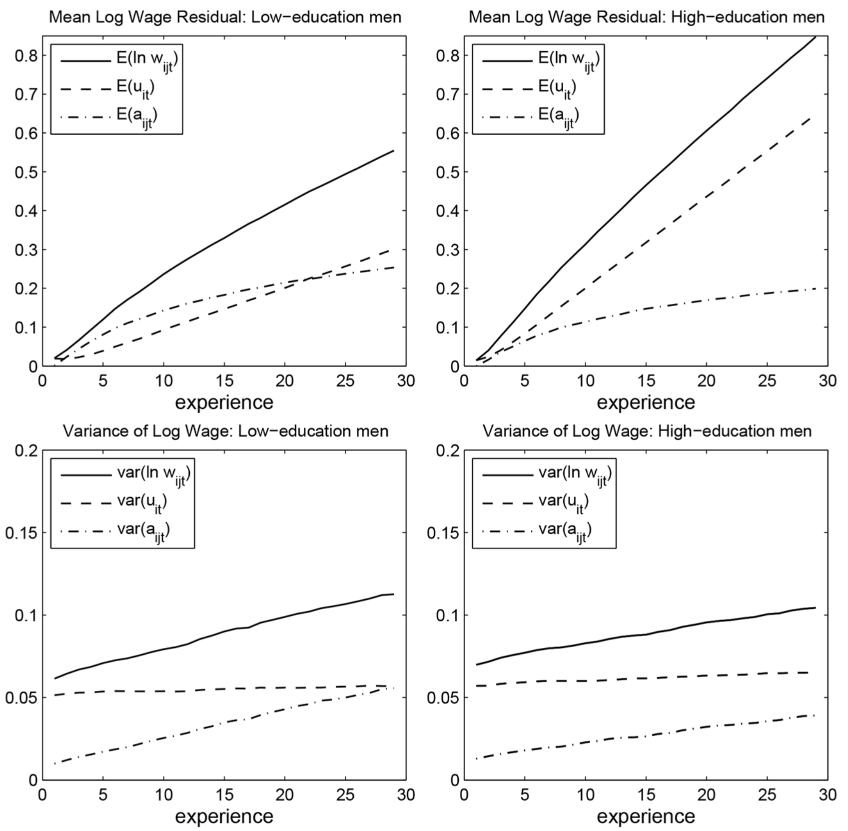

FIG. 6.—Decomposing wage growth and inequality.

as workers climb up the job ladder. The existence of match-level shocks also pushes wages to grow further, because only good shocks are kept and bad shocks could be alleviated through job changes.[48]

The bottom panels of figure 6 show the contributions from match- and individual-level wages to overall wage inequality over time. At the beginning of life, most wage inequality is from variation in individual heterogeneity (i.e., individual's general ability). As a worker accumulates labor market experience, the contribution from the worker-firm match quickly rises as a result of the match shocks and job-to-job transitions. For instance, among low-education men, after 10 years from the beginning of life, the contribution from match-level wages eventually exceeds the contribution from the person-level wages. This implies that differences in labor market histories are an important driving force behind the increasing inequality in early careers.[49]

The model also generates a set of predictions regarding the contributions of different types of risks on cross-sectional inequality. Suppose we have a set of individuals who are employed in both periods $t-1$ and t. We can decompose the inequality of wage growth between periods and t into the following four components:

$$\begin{aligned}\operatorname{var}\left(\Delta \ln w_{ijt}\right) &= \operatorname{var}\left(\Delta a_{ijt}\right) + \operatorname{var}(\zeta_{it}) \\ &= \underbrace{\operatorname{var}\left(E\left(\Delta a_{ijt} | M_{it}\right)\right)}_{\text{between-group variance}} \\ &\quad + \underbrace{\operatorname{var}\left(a_{ijt} - a_{ij't-1} | M_{it} = 1\right) P(M_{it} = 1)}_{\text{match heterogeneity}} \\ &\quad + \underbrace{\operatorname{var}\left(\eta_{ijt}\right) P(M_{it} = 0)}_{\text{match risk}} + \underbrace{\operatorname{var}(\zeta_{it})}_{\text{productivity risk}} .\end{aligned} \tag{16}$$

The first term, between-group variance, represents heterogeneity in the conditional mean match quality with and without job mobility in period t. Match heterogeneity reflects heterogeneity in the offered match quality conditional on moving.[50] Match risk and productivity risk refer to uncer-

[48] Figure A7 shows that the cross-sectional distribution of incumbent match becomes increasingly right-skewed as job tenure increases. When the extent of job-to-job transitions decreases as workers are further up the job ladder, the growth of $E(a_{ijt})$ gradually slows down, generating a concave wage profile.

[49] This result is similar to recent findings from Huggett, Ventura, and Yaron (2011), who argue that policies aiming to improve worker-firm matches are at least as important as education policies aiming to improve initial conditions.

[50] As correctly noted by Low, Meghir, and Pistaferri (2010), part of this term also reflects uncertainty from outside offer draws conditional on current match quality.

tainty in match- and individual-level wage component. The contribution from productivity risk is assumed invariant to job mobility and hence independent of workers' match-level wages in period $t-1$. The relative importance of match heterogeneity and match risk depends on the probability of job mobility and, henceforth, workers' reservation wage.[51]

Table 6 compares the contributions of different wage components to the overall variance of wage growth for both low-education and high-education men. The results are reported at the end of year 1 (period 3), year 4 (period 12), and year 8 (period 24) of the model. At the end of year 1 of the model, about half of the variation of wage growth is due to match-level wage shocks. The remaining half is mainly explained by match heterogeneity and between-group variance. For instance, at the end of year 1 between-group variance accounts for 19.8% and 27.3% of the wage variance among low- and high-education men, respectively. Individual-level productivity risk explains no more than 5% of the overall variance of wage growth. As individuals gain labor market experiences, the wage variance explained by the between-group variance declines significantly. The contribution from match heterogeneity also declines substantially as a result of a declining rate of job mobility. In the meantime, the contribution from match-level risk increases substantially. In order of importance, the key factors explaining the variance of wage growth at the end of year 8 of the model are match-level risk, match heterogeneity, between-group variance, and individual-level productivity risk. At the end of year 8, match-level risk can explain 81.9% of the overall wage variance for low-education men and 67.5% of the overall wage variance for high-education men.

In the model, individual productivity shocks are permanent, but the ex post persistence of match-level shocks depends on the rate of job mobility. It is possible to assess the ex post persistence of match-level shocks. A primitive analysis is provided as follows. Suppose a fraction of a match-level shock is permanent, and the remaining fraction of the match-level shock is an i.i.d. transitory shock. Let $\Delta a_{it} \equiv a_{it} - a_{it-1} = \theta\eta_{it} + (1-\theta)\Delta\eta_{it}$ be the "realized" change in match-level wages between t and $t-1$, where θ is the fraction of the match-level shock that is ex post permanent and, correspondingly, $1-\theta$ is the fraction that is ex post transitory. Then the variance of match-level wage change is given by $\mathrm{var}(\Delta a_{it}) = ((1-\theta)^2 + 1)\sigma_\eta^2$. The fraction of match-level shocks that is permanent, θ, is given by $1 - ((\mathrm{var}(\Delta a_{it})/\sigma_\eta^2) - 1)^{1/2}$. Note that, in the extreme case where there is no job mobility, $\theta = 1$ and all of the changes in the match-level wage are permanent.

[51] The discussion in this section focuses on wage inequality without measurement errors. Measurement errors contribute significantly to the variance of observed quarterly wage changes, although the contribution declines for the inequality of annual wage changes (see sec. C of the appendix for a related discussion).

Table 6
Decomposing the Variance of Wage Growth in Early Careers

	Model Period (4 Months)		
	3	12	24
Decomposition, low-education men (%):			
Between-group variance	19.8	8.7	6.3
Match heterogeneity	22.2	15.9	9.6
Match risk	56.3	73.3	81.9
Individual productivity risk	1.6	2.1	2.2
Decomposition, high-education men (%):			
Between-group variance	27.3	17.7	13.0
Match heterogeneity	23.1	16.6	15.1
Match risk	46.5	61.5	67.5
Individual productivity risk	3.2	4.1	4.5
Mean rate of job mobility:			
Low-education men	.152	.084	.062
High-education men	.133	.093	.062

I find that, at the beginning of careers, match-level shocks are mostly transitory, as workers are able to find better outside offers quickly. A large fraction of match-level shocks are permanent for workers with additional years of experience. Among low-education men, the fractions of match-level shocks that are ex post permanent at the end of year 2 (period 6), year 4 (period 12), and year 8 (period 24) are 39.1%, 56.8%, and 69.3%, respectively. Among high-education men, the fractions of match-level shocks that are ex post permanent at the end of year 2 (period 6), year 4 (period 12), and year 8 (period 24) are 14.7%, 37.3%, and 46.3%, respectively.

B. Value of Job Mobility against Match-Level Shocks

1. *Definition and Measurement*

Consider an individual i employed by firm j at the beginning of period t, just before the realization of the wage shock (η_{ijt}, ξ_{it}) for that period. Let $\tilde{a}_{ijt}(\equiv a_{ijt-1} + c)$ be the match-specific component prior to the match-level wage shock in period t. I measure the value of job mobility as the degree to which the individual is indifferent between particular realizations of a negative match-level shock. I define the difference in continuation values due to the match-level shock as

$$\Delta_{it} = V_t^e(\tilde{a}_{ijt}, u_{it}, S_i) - E_\eta\left(V_t^e(a_{ijt}, u_{it}, S_i | \eta_{ijt} < 0)\right), \tag{17}$$

where $V_t^e(\tilde{a}_{ijt}, u_{it}, S_i)$ is the continuation value without any negative match-level shock and $E_\eta(V_t^e(a_{ijt}, u_{it}, S_i|\eta_{ijt} < 0))$ is the mean continuation value following negative match-level shocks. The term Δ_{it} defines the welfare loss from the match-level wage shock. If $\Delta_{it} = 0$, then the individual is indifferent between the state when the match-level shock arrives and when there is no match-level shock.[52]

To quantify the value of job mobility, I consider a modification to the environment that removes job mobility as a channel of responding to the match-level wage shocks. Under the counterfactual environment, the difference in continuation values due to match-level shocks is given by

$$\widehat{\Delta_{it}} = \widehat{V_t^e}\left(\tilde{a}_{ijt}, u_{it}, S_i\right) - E_\eta\left(\widehat{V_t^e}\left(a_{ijt}, u_{it}, S_i | \eta_{ijt} < 0\right)\right), \tag{18}$$

where $\widehat{V_t^e}$ denotes the continuation value in the counterfactual environment. The counterfactual environment disallows job mobility to respond to match-level shocks by holding the reservation wage for job mobility at the level before the match-level shock is realized in every period of the model. Formally, in every period t and for any draw of match-level shocks (η_{ijt}) and outside offers ($a^o_{ij't}$), the transition probability of match-level wages under the main model is given by

$$f_t\left(a_{ijt} | \eta_{ijt}, a_{ijt-1}\right) = f_t\left(a_{ijt} | M_{it}, \eta_{ijt}, a_{ijt-1}\right) h_t\left(M_{it} | \eta_{ijt}, a_{ijt-1}\right), \tag{19}$$

where job mobility (M_{it}) can respond to match-level shocks (η_{ijt}) via the h density. When job mobility is removed as a channel of responding to the match-level wage shocks, the counterfactual distribution, denoted by $\hat{f}$, is given by

$$\hat{f}_t\left(a_{ijt} | \eta_{ijt}, a_{ijt-1}\right) = f_t\left(a_{ijt} | M_{it}, \eta_{ijt}, a_{ijt-1}\right) h_t\left(M_{it} | 0, a_{ijt-1}\right), \tag{20}$$

where the likelihood of job mobility (the h density) is evaluated holding η_{ijt} at zero. The density function $\hat{f}$ is used to define the value function in the counterfactual environment in each period.[53]

In the model, job mobility may reduce the welfare cost of match-level shocks via two interrelated channels. Following the negative match shock, the worker's reservation match becomes lower than the reservation match without the shock. There is a set of wage offers that are acceptable after

[52] Relative to match-level wage shocks, I find that individual-level wage shocks have very small welfare impacts on average. For this group of young male workers, the size of the individual-level wage shocks appears to be too small to have any sizable impact on workers' behavior and welfare.

[53] In this paper, the value of job mobility is defined in terms of how job mobility affects the welfare loss from the match-level wage shock, not how job mobility improves the overall level of welfare. Even without match-level shocks, the individual would be worse off if job mobility is removed because the individual has to forego outside offers that may provide improvement in match quality. The primary focus of the paper is not the value of job mobility per se but the component of that value that is related to the welfare effects of match-level wage shocks. This is similar to what has been used in the literature to define the "insurance" value of individual actions against different types of shocks (e.g., Kaplan 2012).

the match-level shock, which would not have been acceptable without the match-level shock. In the meantime, following negative match-level shocks, search intensity would increase to take advantage of the increasing marginal benefit from job mobility. This increases the rate of offer arrival and further strengthens the value of job mobility as a channel to reduce the welfare cost of match-level shocks. The counterfactual environment thereby disallows job mobility to respond to match-level shocks falling in this range while keeping the wage distribution conditional on job mobility unchanged.

The value of job mobility as a channel against negative match-level shocks can be defined as

$$\xi_{it} = 1 - \frac{\Delta_{it}}{\widehat{\Delta}_{it}}, \tag{21}$$

where ξ_{it} is the proportional decrease in the average cost of negative match-level shocks due to the option of job mobility. Note that ξ_{it} is heterogenous across workers because it depends on both match- and individual-level wages. If ξ_{it} is very close to 0, then the welfare loss from the negative match shock is almost identical whether job mobility is allowed or not. In this case, job mobility is not a valuable channel against the match-level shock. If ξ_{it} is close to 1, then the welfare loss from the negative match shock is small when job mobility is allowed (relative to the welfare loss when job mobility is disallowed), which implies that job mobility is a highly valuable channel against the match-level shock.

2. *The Value of Job Mobility*

I use the estimated model to calculate the value of job mobility for individuals with four different combinations of the individual- and match-level wages. I consider two types of individuals, u^H (large individual-level wage) and u^L (small individual-level wage), who are matched to jobs with high (a^H) and low (a^L) match quality.[54] Column 1 of table 7 shows the value of job mobility (ξ_{it}), defined in terms of how much the average cost of match-level shocks is reduced due to the availability of job mobility (eq. [21]). I find that job mobility can reduce the average cost of a match-level shock, particularly for individuals whose match-level wages are low. For instance, for a low-education individual with a high individual-level wage but matched to a job with a low match-level wage, job mobility can reduce the average welfare cost of negative match-level shocks by as much as 63.8%. By contrast, if the same individual worked in a job with a high match-level wage, then the value of job

[54] The value of job mobility is computed at the end of year 4 (period 12) in the model. The high and low values of individual- and match-level wages are defined at the 90th and 10th percentile of the corresponding distributions in period 12, respectively.

Table 7
Value of Job Mobility in Response to Match-Level Wage Shocks

Wage Components (Individual, Match)	Baseline (1)	Expand UI (2)	Reduce Cost of Search: Unemployment (3)	Reduce Cost of Search: On the Job (4)
A. Low-education men:				
u^L, a^L	.581	−.107	−.008	.023
u^H, a^L	.638	−.001	.000	.019
u^L, a^H	.097	−.011	−.001	.005
u^H, a^H	.104	.000	.000	.004
B. High-education men:				
u^L, a^L	.579	−.118	−.016	.012
u^H, a^L	.675	−.017	−.001	.009
u^L, a^H	.166	−.013	−.003	.004
u^H, a^H	.179	−.001	.000	.003

NOTE.—u^L (a^L) and u^H (a^H) are, respectively, the individual (match) component of wage at the 10th and 90th percentiles in period 12 of the model. Columns 2–4 report differences relative to col. 1. UI = unemployment insurance.

mobility reduces substantially to 10.4%. Relative to workers whose match quality is high, workers located in the bottom of the match quality distribution respond more to a given negative match shock.[55]

Holding match quality fixed, I find that workers whose individual productivity is high benefit more from job mobility (in terms of reducing the average welfare cost of negative match-level shocks) than workers whose individual productivity is low. For instance, among low-educated workers with the same match quality at a^L, the values of job mobility are 63.8% and 58.1% for workers with high and low levels of individual productivity, respectively. The reason for this difference is different reservation match values for employment: workers with high individual productivity have lower reservation match quality for employment than workers with low individual productivity. For a given large and negative match-level shock, workers with low individual productivity are more likely to quit for unemployment, thereby reducing the value of job mobility in reacting to this shock.

3. *The Role of Search Costs and Unemployment Benefits*

Columns 2–4 of table 7 report how the value of job mobility might be affected by changes in the model environment. I focus on the following three

[55] Formally, this conclusion depends on the relative position of the match quality distribution and the offered match distribution. For instance, fig. A7 shows, for individuals who are already at the top of the job ladder, that job mobility could be useful only for mitigating large negative match-level shocks. Endogenous search intensity would strengthen the reaction to negative match-level shocks.

scenarios: (i) a one-third increase in the replacement rate of unemployment benefits from 40% to 52% (col. 2), (ii) a decrease in the marginal cost of unemployment search (col. 3), and (iii) a reduction in the marginal cost of on-the-job search (col. 4).[56]

Both unemployment and job mobility are channels that workers may use to alleviate negative match-level shocks. I find that policies that make unemployment more attractive reduces the value of job mobility. For instance, the expansion of unemployment benefits reduces the value of job mobility (col. 2). The reduction is particularly large for the group of workers with low-individual productivity and low match quality. Among low-education men, the value of job mobility for these workers is reduced by 0.107, or 18.3% relative to the initial level. Among high-education men, the value of job mobility for these workers is reduced by 0.118, or 20.4% relative to the initial level. A reduction in the cost of unemployment search has the same qualitative effects on the value of job mobility (col. 3), although the effects are small relative to the effects of the expansion in unemployment benefits. Finally, column 4 shows that a decrease in the cost of on-the-job search increases the value of job mobility, and the increase is relatively more pronounced for individuals with low match quality.

To further explore the interaction between job mobility and unemployment benefit in alleviating match-level shocks, table 8 reports the welfare cost of match-level shocks under four different model environments. The baseline column (col. 1) reports the welfare cost of match-level shocks where job mobility is removed from a channel of responding to the match-level wage shocks ($\widehat{\Delta_{it}}$). Columns 2 and 3 report the differential welfare cost after allowing for job mobility to respond to match-level shocks ($\Delta_{it} - \widehat{\Delta_{it}}$) and raising unemployment income, respectively. Column 4 reports the interaction effects from adding both job mobility and raising unemployment income simultaneously. I find that an increase in unemployment income alone can also reduce the welfare cost of match-level shocks without job mobility (col. 3). However, relative to job mobility (col. 2), the reduction in the welfare cost tends to be small. Therefore, unemployment is a useful channel to alleviate negative match-level shocks, but it is less valuable compared with job mobility. The positive interaction effects between job mobility and unemployment (col. 4) implies that job mobility is less valuable when there is higher unemployment income (adding cols. 2 and 4), and raising unemployment income offers less welfare gains in the presence of job mobility (adding cols. 3 and 4). In fact, the value of higher unemployment income is largely crowded out by job mobility (adding cols. 3 and 4). Therefore, the value of

[56] The reduction in the marginal cost of search is set such that the one-third increase in unemployment insurance benefits combined with the reduction in search costs implies a constant net flow utility when the rate of offer arrival is equal to 1.

Table 8
Welfare Cost of Match-Level Wage Shocks

Wage Components (Individual, Match)	Baseline (1)	Job Mobility (2)	Expand UI (3)	Interaction Effects, JM + UI Expansion (4)
A. Low-education men:				
u^L, a^L	.538	−.313	−.110	.109
u^H, a^L	.622	−.396	−.002	.002
u^L, a^H	.991	−.097	−.012	.012
u^H, a^H	.999	−.104	.000	.000
B. High-education men:				
u^L, a^L	.442	−.256	−.097	.097
u^H, a^L	.575	−.388	−.029	.028
u^L, a^H	.980	−.163	−.015	.015
u^H, a^H	.995	−.179	−.002	.002

NOTE.—u^L (a^L) and u^H (a^H) are, respectively, the individual (match) component of wage at the 10th and 90th percentiles in period 12 of the model. Columns 2 and 3 report differences relative to col. 1. Column 4 reports the interaction effects of job mobility (JM) and unemployment insurance (UI) expansion. The value of job mobility when UI is high is given by adding cols. 2 and 4. The value of increasing unemployment benefits in the presence of job mobility is given by adding cols. 3 and 4. See Sec. VI.B for details.

unemployment benefits against match-level shocks could be overstated without accounting for endogenous job mobility response to shocks.[57]

This exercise, albeit speculative (e.g., because the partial equilibrium nature of the model), highlights the importance of distinguishing sources of wage shocks and modeling job mobility behavior against match-level wage shocks. Policies that make unemployment benefits more generous increase the reservation match quality for employment. Consequently, workers are incentivized to switch from using job mobility to unemployment as a channel to react to a certain range of match-level shocks. The crowding-out effects are especially pronounced among the group of workers with low-individual productivity and low match quality.[58] Relative to offering more generous unemployment income, policies that subsidize the cost of unemployment search have a relatively minor impact on the value of job mobility.

VII. Conclusion

In this paper, I estimated a dynamic structural model of job mobility and employment jointly with a stochastic wage process. I considered two sources

[57] Unemployment benefits still have welfare value of insuring against other types of risk, such as job destruction. Job mobility is not a channel that workers can use to react upon layoff.

[58] For this group of workers, the threshold match value for employment is low, and they are most likely to fall back to unemployment for a wide range of negative match-level shocks.

of wage shocks, shocks at the worker-firm-match level and shocks at the individual level that persist across jobs, and modeled their effects on dynamic individual behaviors, such as employment, job mobility, and job search efforts. The estimation results suggest that wage risk at the match level is the dominating type of risk facing employed individuals. In order of importance, the key factors explaining the variance of wage growth at the end of year 8 of the model are match-level risk, match heterogeneity, between-group variance, and individual-level productivity risk. A larger fraction of match-level shocks are permanent for workers with more years of experience. For instance, among low-education men the fractions of match-level shocks that are ex post permanent at the end of year 2 and year 8 are 39.1% and 69.3%, respectively.

I showed that job mobility is a valuable channel in response to the match-level wage shocks in early careers. The value is particularly large for individuals at the bottom of the job ladder (holding individual productivity fixed) and individuals of low productivity (holding the match quality fixed). The interaction effects between job mobility and unemployment implies that job mobility is less valuable when unemployment income is high and raising unemployment income has less welfare gains in the presence of job mobility. The interaction effects are strongest for the group of workers with low individual productivity and low match quality. For instance, among low-education men, a more generous unemployment income reduces the value of job mobility for these workers by 18.3% relative to the initial level. Unemployment income also provides some value in terms of reducing the welfare cost of match-level shocks, but only when job mobility is removed from a channel of responding to these shocks.

Recovering the true wage risk facing individuals from their choices is complex. While this paper takes a step to separate match-level risk from individual-level risk by modeling job mobility, it has several limitations that can be extended in future research. First, the modeling of job mobility decisions is simple and highly stylized. For instance, jobs could differ in other aspects besides match quality. Modeling transitions across jobs that differ explicitly in wage risk, return to tenure, or hours of work is desirable and left for future research. Each extension would add another state variable in the model and require a careful specification of the preference structure. Second, in the current paper, the productivity of a worker is known to the firm in each period. Empirical work on the implications of learning for wage dynamics within and across jobs and for job mobility is a promising area for future research. This will provide some structural interpretation of the match-level wage shocks that are considered important in this paper (Farber and Gibbons 1996). Finally, an important avenue for future research is to analyze the relation between job mobility and other channels that workers can rely on in response to labor market risks and to quantify their relative value in reacting against different types of shocks.

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