Risk and Return Trade-Offs in Lifetime Earnings

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This paper documents differences in lifetime earnings risk across occupations due to wage risk, employment risk, and midcareer occupation changes, which can mitigate other shocks. Total lifetime earnings risk varies considerably across starting occupation, and riskier occupations pay more in expectation. The average worker would give up at least 9% of total lifetime earnings in the least certain occupation to reduce the riskiness of that occupation to the level of the safest starting occupation. The insurance value of occupational mobility is quantitatively important. With mobility, workers absorb only 60%, on average, of negative occupation-specific wage shocks.

I. Introduction

Rational, risk-averse workers choosing between occupations should consider not only their expected earnings along each path but also the uncertainty around that expectation. In this paper, I quantify the differences in lifetime earnings risk across occupations and characterize the relationship between this risk and expected lifetime earnings. The slope of this risk-return tradeoff describes how much earnings workers are on average willing to forego

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in order to decrease earnings uncertainty, which in turn has implications for the optimal design of social safety net programs and progressive tax structures that can reduce earnings risk. Compensation for earnings risk can also help explain why similar workers earn different wages in different occupations.

Lifetime earnings risk encompasses uncertainty about wages, employment, and future transitions between occupations. The interactions between these components of risk affect the overall riskiness of an occupation. Occupation changes can represent an added source of risk if workers move unwillingly after losing their job and lose the value of accumulated specific skills in the process. Occupational mobility also provides an important insurance mechanism by allowing workers to escape some negative wage shocks. The total earnings risk of an occupation therefore depends in part on the endogenous job choices that workers make in response to shocks. Considering only the variance of wage shocks, which has been the focus of much of the previous work on this question, may over- or understate lifetime earnings risk because it omits both employment risk and the insurance provided by job mobility.

To capture wage shocks and the multifaceted relationship between risk and occupation mobility, I construct a model of the labor market with multiple occupations, search frictions, and occupation-specific returns to tenure and shocks to wages. Risk-averse workers face exogenous job loss risk and can also choose to quit and search for work in new occupations. Job offers from all occupations arrive exogenously for unemployed workers. I estimate the parameters that govern this model using method of moments and simulated method of moments as well as data from the Panel Study of Income Dynamics (PSID) and the Current Population Survey (CPS). I then use this model to simulate streams of lifetime earnings for workers starting in each occupation. The simulated workers are ex ante identical in skills and preferences. Over their working lives they receive wage and employment shocks and maximize their expected lifetime utility, which may involve changing occupations. The variance of these simulated streams of earnings therefore represents a total measure of earnings risk that includes employment uncertainty, wage uncertainty, and the interaction between these two when workers behave optimally within the model.

This structural approach to estimating lifetime earnings risk has several advantages. First, it overcomes the practical limitation that US data sources rarely cover the full working lives of individuals. Second, even if I observed full earnings paths for a large sample of workers, the variance of these streams would reflect a combination of exogenous shocks, endogenous responses to these shocks, and other differences in workers' skills and preferences. Some workers may earn more than others in any occupation or experience faster wage growth. An individual worker might decide to quit a lucrative job to pursue another less well paid but more emotionally satisfying career. None of these differences reflect earnings uncertainty. By carefully estimating the sources of wage and employment risk and then simulating the best responses of workers with relatively simple preferences, I isolate unavoidable earnings risk from these other sources of earnings variation. Finally, I can use this model to decompose the roles of wage risk, employment risk, and occupational mobility in determining total lifetime risk.

This method yields three key findings. First, lifetime earnings risk varies considerably across starting occupations. Among workers with some college education, those who begin in legal occupations face more than twice as much lifetime earnings risk as those who begin in sales. Both wage and employment risk vary across occupations, but they are not closely aligned. The standard deviation of permanent wage shocks is an order of magnitude higher in agriculture than in occupations with less wage risk. However, agricultural workers have the lowest probability of losing their job—less than half the risk of household and other maintenance workers.

Second, workers appear to recognize this variation in earnings risk and demand compensation for it. Across starting occupations, mean lifetime earnings are positively correlated with earnings uncertainty. Additionally, workers who are more risk averse, as measured by a survey instrument, sort into lower-risk occupations. This sorting suggests that the observed risk-return trade-off likely understates the willingness of individual workers to pay to reduce the variance of lifetime earnings. The slope of the observed risk-return frontier reflects the risk aversion of the marginal worker who accepts a job at each level of risk. Since the risk tolerance of these marginal workers is increasing in earnings risk, the relationship between the mean and variance of lifetime earnings is flatter than the slope of any single worker's indifference curve. The average worker would give up at least \$8,500 per year—9% of mean earnings for lawyers—to reduce the uncertainty of that high-earning but high-risk occupation to the level of sales workers, one of the least risky occupations.

Third, occupational mobility is a quantitatively important insurance mechanism to reduce earnings risk. The overall riskiness of most occupations is lower in the full model than in a counterfactual model without occupational mobility. While occupation changes are costly, these costs are balanced by the option to escape low wage shocks. To illustrate this mechanism, I simulate the effects of large occupation-specific wage declines. Following a 20% drop in wages in their current occupation, about half of workers quit and search for new jobs. Because of this mobility, earnings for workers who begin in the affected occupation fall on average by only 12% following the shock. The effect of these simulated wage shocks on total lifetime earnings is hump shaped in worker age. Young workers, who have not yet built up substantial occupation tenure, face low costs of changing occupations after the shock. Older workers have too few working years left for the shock to substantially affect total lifetime earnings. The highest costs are born by workers who are in their thirties when the shock hits.

The idea that earnings in an occupation should reflect compensation for characteristics of that occupation was first articulated by Smith (1776/2008) and was formalized by Rosen (1986). Kuznets and Friedman (1939) proposed a positive relationship between the mean and variance of incomes among professional workers. Since then, several papers have found a positive relationship between cross-sectional or single-period variance of wages and mean wages across occupations, including King (1974), Hartog and Vijverberg (2007), and McGoldrick and Robst (1996). However, these papers miss the correlation in shocks over time and ignore employment risk and occupation transitions. Cubas and Silos (2017) use a multiperiod measure of wage risk across industries without the addition of employment risk and also find a positive relationship between risk and average wages.

In this paper, I incorporate a more detailed approach to isolating and estimating wage uncertainty within a life-cycle model with job mobility in the style of Moffitt and Gottschalk (2002), Low, Meghir, and Pistaferri (2010), Buchinsky et al. (2010), Altonji, Smith, and Vidangos (2013), and Guvenen and Smith (2014). Pavan (2011) incorporates moves between jobs and between careers into this style of model but does not allow sources of risk to vary by occupation or industry. I build on these papers by measuring differences in risk across occupations and by building a total measure of occupation-specific risk that combines wage and employment uncertainty. Low, Meghir, and Pistaferri (2010), Vereshchagina and Hopenhayn (2009), and Neumuller (2015) all point out that job changes create an option value by allowing workers to escape low wage shocks. Recently, Liu (forthcoming) estimates that a large share of wage shocks faced by young workers are job specific, implying that they can be mitigated by changing jobs. I know of no other paper that quantifies the share of wage shocks that the average worker avoids through this mobility.

The next section presents a model of workers' optimal labor supply and consumption choices in the face of uncertain earnings and describes the solution to this model. Section III discusses the data, the estimation method, and the parameter estimates. Section IV analyzes the relationship between expected lifetime earnings and earnings riskiness. Section V explores the role of occupation mobility in mitigating earnings risk, and Section VI concludes.

II. A Life-Cycle Model of Career Choices and Earnings

I model a labor market with search frictions in which jobs are differentiated by occupation and workers face multiple sources of earnings risk from shocks to wages and the possibility of job destruction. Unemployed workers receive job offers from all occupations and may choose to accept an offer that involves a change in occupation from their previous work. I do not include an out-of-the-labor-force state in which people neither work nor search for work.[1] Workers are risk averse and can borrow and save to smooth over earnings fluctuations. My aim is to model working life parsimoniously while still capturing the major sources of lifetime earnings uncertainty and allowing workers to mitigate negative wage shocks through occupational mobility.

All variations in earnings and earnings uncertainty in this model come at the occupation level, with no distinction between different employers or industries within an occupation. Shaw (1984) and Kambourov and Manovskii (2009) find that while firm, industry, and occupation tenure all affect wages, occupation tenure is the most important single determinant. I use 19 occupation categories, based on the 2000 census major occupation groups, listed in table A1 in the appendixes, available online.

In this model, workers are assigned a starting occupation, although they may later transition to other occupations. In reality, workers also choose their starting occupations. These choices by risk-averse workers drive the relationship between riskiness and expected earnings, although the sorting of workers who are more risk tolerant into higher-risk occupations will also mute any observed compensating wage differential for additional risk. The aim of this working model is not to re-create this initial choice but rather to capture average earnings and earnings risk conditional on first occupation. Without incorporating differences across occupations in the cost of initial training, the arduousness of the work, and other factors, workers in my model would all flock to the highest-paying professions, like law and health. While in my simulations, as in life, workers from lower-paying occupations, like community service, are more likely to eventually change occupations, I prevent wholesale herding into a few occupations by making search costly and by matching the distribution of new offers for workers in each occupation to observed transition rates between occupations.

A. Wages

The expected wage of a worker i employed at time t in occupation $k_{it} \in \{1, \dots, K\}$ depends on his total labor market experience, x_{it}; his tenure in his current occupation, τ_{ikt}; and, following Abbott et al. (2013), his age, s_{it}. Realized wages, W_{ikt}, depend on these observed characteristics; fixed effects for the worker, η_i, and his current occupation, μ_k; and four stochastic components:

$$\log(W_{ikt}) = \mu_k + \eta_i + \phi(x_{it}, s_{it}) + \psi_k(\tau_{ikt}) + \alpha_{ik} + \varepsilon_{kt} + \zeta_{it} + \xi_{it}. \quad (1)$$

The effects of occupation tenure differ by occupation. This variation and the occupation fixed effect generate differences in expected wages across occupations.

[1] In my estimation, I focus on men between the ages of 22 and 55, for whom this omission is relatively benign.

On starting in a new occupation, workers draw a match quality, $\alpha_{ik} \sim N(-(1/2)\sigma_\alpha^2, \sigma_\alpha^2)$, that remains fixed during their time in that occupation. The distribution of match is the same across occupations and individuals. This worker-occupation match captures an additional level of uncertainty about untried occupations and will generate some churning in the early periods of working life as workers who are poorly matched with their starting occupations quit and search elsewhere.

Wages for all workers in occupation k at time t depend on an AR(1) component, ε_{kt}, with occupation-specific persistence ρ_k and innovation $e_{kt} \sim N(-(1/2)\sigma_{ek}^2, \sigma_{ek}^2)$:

$$\varepsilon_{kt} = \rho_k \varepsilon_{kt-1} + e_{kt}. \tag{2}$$

This shock captures fluctuations in productivity or demand that affect all workers in each occupation. Workers can escape negative occupation shocks by searching for work in other occupations. I do not separately model a fully macroeconomic shock, so business cycle variations will be captured in this occupation-level shock.[2]

Workers also experience idiosyncratic and fully permanent shocks:

$$\zeta_{it} = \zeta_{it-1} + u_{it}. \tag{3}$$

While the variance of this idiosyncratic shock is also occupation specific, $u_{it} \sim N(-(1/2)\sigma_{ku}^2, \sigma_{ku}^2)$, workers carry their current level of this stochastic component between occupations, so they cannot escape negative shocks through occupation changes.[3] Carrying this component across occupations makes sense if it consists mainly of general skills and physical capacity or if a worker's most recent wage affects his bargaining power at his next job.

Finally, employed workers experience a transitory wage shock with occupation-specific variance, $\xi_{it} \sim N(-(1/2)\sigma_{k\xi}^2, \sigma_{k\xi}^2)$. Idiosyncratic permanent and transitory shocks, occupation shocks, and match quality are all independent of one another.

B. Employment and Earnings

Individuals live for L periods and may work for the first T of them. In the estimation, each period is a quarter, and I set $L = 160$ and $T = 120$. Prior to the first working period, $t = 0$, individuals receive a starting occupation. In

[2] Estimating the degree to which these occupation shocks covary with each other or with a macro business cycle shock is beyond the scope of this paper but would be a valuable extension for future work. The occupation wage effects could also follow time trends, but as I discuss in Sec. III.A, there is little evidence that they do.

[3] The random walk assumption is necessary for estimation. With a general autoregressive model (AR) process, the change in a worker's wages could depend on the variance of all his past shocks and therefore his complete occupation history, which I do not observe in the data.

the first working period, $t = 1$, all individuals are employed in that occupation and learn and receive their starting wage. This framework for the start of working life resembles a world where individuals sort into careers while still in school and have a position lined up by the time they are ready to begin work.

In all subsequent working periods, employed workers face an occupation-specific probability $0 \leq \delta_k \leq 1$ of losing their job and entering unemployment. To greatly ease the computational burden I do not allow workers to receive outside job offers while working, but workers may quit if they wish to search for work in other occupations. Unemployed workers who were most recently employed in occupation k receive a job offer from their current occupation with per-period probability $0 \leq \lambda_{ck} \leq 1$ and from a new occupation with probability $0 \leq \lambda_{nk} \leq 1 - \lambda_{ck}$. The per-period probability that a worker most recently employed in occupation k receives an offer from a new occupation k' is defined as $\lambda_{kk'}$, where $\Sigma_{k' \neq k} \lambda_{kk'} = \lambda_{nk}$. Unemployed workers may choose to accept an offer if they receive one or remain unemployed.

When not employed, workers receive a fraction, b, of their wage. This estimated fraction of wages captures both monetary unemployment benefits and the monetary equivalent of other benefits of not working. Earnings therefore depend on employment status, $N_{it} \in \{0, 1\}$, and are given by

$$Y_{ikt} = \begin{cases} W_{ikt} & N_{it} = 1, \\ bW_{ikt} & N_{it} = 0. \end{cases} \tag{4}$$

Expected wages for unemployed workers, in their current occupation, continue to be affected by the aggregate wage shocks of their most recent occupation, ϵ_{kt}, but they do not experience further idiosyncratic shocks. The first assumption reflects the interpretation of ϵ_{kt} as occupation-wide variations in potential worker productivity, the evolution of which does not depend on the employment status of one worker. The second assumption reflects the idea that many of these individual shocks come from new skills learned or capacities lost while working and should therefore not evolve during unemployment. Workers accumulate labor market experience whenever they are employed, and this experience does not depreciate during unemployment spells.[4] Workers accumulate occupation-specific tenure while

[4] Many studies—recently Davis and Von Wachter (2011) and Jarosch (2015)—have documented an additional negative "scarring" effect of unemployment on subsequent wages. Estimating such an effect is difficult in this model in conjunction with estimating worker-occupation match effects. Neal (1995) finds that all of this cost of unemployment can be explained by a loss of specific human capital for workers who change industries. This effect is captured in this model by the loss of tenure. More recent studies suggest that some residual cost of unemployment re-

working in that occupation. Tenure does not depreciate during unemployment, but it is lost when a worker changes occupations. For example, a worker who spends 5 years in manufacturing and then loses his job will start with 5 years of tenure if he takes a new job in manufacturing but no tenure if he takes a new job in sales. If he later returns to manufacturing from sales he will restart with no tenure. This assumption is necessary for the estimation since I do not observe the full occupation histories of most workers in my data.

Finally, during retirement individuals receive a fraction, *pen*, of their earnings in their last period of work as a pension. The worker has no uncertainty about this pension once his earnings in his last period of working life are revealed. If the worker is employed in period T, this pension is $pen \cdot W_{ikT}$. If he is not employed in period T, his pension is $pen \cdot b \cdot W_{ikT}$. Each working period starts with shocks to wages, job destruction shocks for some employed workers, and new offers for some unemployed workers. Workers then choose to quit, to accept a job offer if they have one, and how much to consume.

This model ignores any heterogeneity in jobs within occupation. Earlier studies, such as Topel and Ward (1992) or Pavan (2011), demonstrate that both transitions between occupations and transitions between jobs in the same occupation are important for wage growth, particularly early in the career. Abstracting from these issues is a necessary simplification to estimate the rich heterogeneity in riskiness across occupations. The wage process modeled here will capture the returns to intraoccupation job mobility in two ways. The estimated returns to occupation tenure will combine true returns to occupation tenure, true returns to job tenure, and the average effects of searching for better-matched jobs within an occupation. The estimated idiosyncratic wage shocks (σ^2_{ku} and $\sigma^2_{k\xi}$) will capture both shocks to wages within a job and variation in wages due to job changes within an occupation. Another implication of this simplification is that the model may overpredict occupation changes because the simulated workers have no opportunity to improve their job match without also changing occupations.

C. Consumption

I assume that individuals have standard time-separable constant relative risk aversion utility over consumption with coefficient of relative risk aversion γ and discount rate β. I further assume that individuals get no utility from leisure.[5] Individuals can save and borrow over their lives at a constant

mains for workers who return to the same occupation and industry. In practice, this cost will be reflected, in a reduced-form way, in the relatively low income stream during unemployment (I set $b = 0.2$).

[5] The amount of hours worked and the flexibility of hours represent another important dimension of differences across occupations that may affect how workers

risk-free interest rate r, but they cannot buy state-dependent assets to insure against idiosyncratic earnings risk. The worker's problem is therefore to choose each period his consumption, C_{it}; employment; and occupation to maximize

$$\max_{C_{it}, N_{it}, k_{it}} E_t \left[\sum_{s=t}^{L} \beta^{s-t} \frac{C_{is}^{1-\gamma}}{1-\gamma} \right], \tag{5}$$

subject to a terminal asset condition $A_{iT} \geq 0$ and the dynamic budget constraint

$$A_{it+1} = (1 + r)(A_{it} + Y_{ikt} - C_{it}). \tag{6}$$

I assume that everyone begins life with no assets, $A_{i1} = 0$. A worker's ability to borrow is subject to a natural borrowing constraint, as in Aiyagari (1994), equal to the discounted value of worst-case earnings for all remaining working periods.[6] Workers cannot borrow against their pensions, $a_{T+1} \geq 0$. Prohibiting all borrowing would make workers less willing to quit and search for new jobs, since they would have to first build up savings to cover low earnings during unemployment.

Because wages are expected to grow over the lifetime and workers are impatient, individuals will prefer to consume more than their earnings early in life. Working against that inclination, uncertainty about future earnings will cause people to build up precautionary savings to guard against negative shocks (Carroll and Kimball 2008). In practice, workers accumulate substantial debt early in life to fund the costly search for a high-wage match.

D. Model Solution

The solution to the multiperiod model consists of workers' optimal choices of consumption and labor each working period. There is no analytical expression for this policy rule. Instead, I solve the model numerically working backward from the analytic solution for consumption during retirement. I describe the main features of the solution here and provide more detail in appendix A.

The consumption and employment decisions can be viewed sequentially: workers first choose consumption to optimize the value of each employment state given the state variables. They then choose among employment

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sort into them. Including disutility from work and variation in hours worked across occupations is a nontrivial but interesting extension of this model.

[6] I define the worst-case scenario as being unemployed for all remaining periods with the occupation-specific AR(1) component held fixed at the 0.01 percentile in each occupation (between 0.8 and 0.92 in levels). The probability of receiving less than this income for all remaining periods is very small, and in practice the simulated workers never violate the no-Ponzi condition.

situations, substituting this optimal consumption into the value equations. The value of an employment situation is a function of assets, A_{it}, and the determinants of wages. Following Carroll (2004), I factor current income out of the value functions.[7] This transformation is computationally useful because it reduces the state variable set to the determinants of income growth.

Growth in income, $g_{t+1} = Y_{t+1}/Y_t$, depends on the employment situation this period and last:

$$g_t = \begin{cases} e^{\phi'(x_{it}, s_{it}) + \psi'_k(\tau_{ikt}) - (1-\rho_k)\varepsilon_{kt-1} + e_t + u_t} & N_{t-1} = N_t = 1, \\ be^{\phi'(x_{it}, s_{it}) + \psi'_k(\tau_{ikt}) - (1-\rho_k)\varepsilon_{kt-1} + e_t + u_t} & N_{t-1} = 1, N_t = 0, \\ e^{\phi'(s_{it}) - (1-\rho_k)\varepsilon_{t-1} + e_t} & N_{t-1} = N_t = 0, \\ \frac{1}{b} e^{\phi'(s_{it}) - (1-\rho_k)\varepsilon_{t-1} + e_t} & N_{t-1} = 0, N_t = 1, k_{t-1} = k_t, \\ \frac{1}{b} e^{\phi'(s_{it}) - \psi_k(\tau_{kt-1}) + \mu_{kt} - \mu_{kt-1} + \alpha_{kt} - \alpha_{kt-1} + \varepsilon_{kt} - \varepsilon_{kt-1}} & k_{t-1} \neq k_t. \end{cases} \tag{7}$$

Income growth after a period of employment includes predictable growth in the returns to age, experience, and tenure; predictable decay of the stochastic occupation component; and new occupation and individual shocks. Workers who were unemployed last period and remain in the same occupation, either employed or unemployed, are affected only by the change in their age and the occupation effect. Workers moving in and out of unemployment experience large changes in income as they move from earning b fraction of their wage to their full wage. Finally, individuals moving from unemployment to employment in a new occupation lose the effects of their accumulated tenure in their old occupation and switch to a new occupation match quality and occupation fixed and stochastic effects.[8] I assume that age and tenure have quadratic effects on earnings, while total labor market experience has a linear effect. Under this assumption, total work experience, x_{it}; the individual fixed effect, η_i; and the level of the permanent shock, ζ_{it}, affect the level of wages but not expected income growth. These components are therefore not state variables for the policy rule.[9] The determinants of income growth are $\Omega_{it} = \{s_{it}, \tau_{ikt}, \varepsilon_{kt}, \alpha_{ik}\}$.

[7] The derivation of this reformulation is described in app. A.

[8] I have omitted the transitory wage shock here, as I will in the simulations. The estimate of the standard deviation of these shocks is large but likely includes substantial measurement error in addition to true transitory wage variation. In any case, fully transitory shocks do not have a meaningful effect on lifetime risk.

[9] Note that the borrowing constraint is also defined in terms of a fraction of current income, so that constraint does not add to the state variable space.

First, consider the transformed value of being employed today in occupation k:

$$v_t^{1,k_t}(a_t, \Omega_t) = \frac{V_t^{1,k_t}(A_t, \Omega_t)}{Y_t^{1-\gamma}}, \tag{8}$$

where $a_t = A_t/Y_t$. Next period, an employed worker will see his job exogenously destroyed with probability δ_k. If his job is not destroyed, he can choose to remain employed or to quit to look for other work. The value function for a worker in this situation is therefore

$$\begin{aligned} v_t^{1,k_t}(a_t, \Omega_t) = \max_{c_t}\Bigg\{&\frac{c_t^{1-\gamma}}{1-\gamma} + \beta\delta_{k_t}E\left[g_{t+1}^{1-\gamma}v_{t+1}^{0,k_t}(a_{t+1}, \Omega_{t+1})\right] \\ &+ \beta(1-\delta_{k_t})E\max_{N_{t+1}}\Big[g_{t+1}^{1-\gamma}v_{t+1}^{0,k_t}(a_{t+1}, \Omega_{t+1}), \\ &\qquad g_{t+1}^{1-\gamma}v_{t+1}^{1,k_t}(a_{t+1}, \Omega_{t+1})\Big]\Bigg\}, \end{aligned} \tag{9}$$

where g_{t+1} depends on the labor supply choice and expectations are taken conditional on information at time t. Assets and occupation tenure next period are known conditional on the worker's choices today. The expectation operator denotes his uncertainty about shocks to next period's wages. While the level of the permanent wage shock does not affect his choice, the innovation to this shock is part of g_{t+1}.

If a worker is unemployed in period t, then in period $t+1$ he may receive a job offer from his current occupation with probability λ_{ck}, a job offer from a new occupation with probability λ_{nk}, or no job offers. The value function for an unemployed worker in occupation k is therefore given by

$$\begin{aligned} v_t^{0,k_t}(a_t, \Omega_t) = \max_{c_t}\Bigg\{&\frac{c_t^{1-\gamma}}{1-\gamma} \\ &+ \beta(1-\lambda_{ck_t}-\lambda_{nk_t})E\left[g_{t+1}^{1-\gamma}v_{t+1}^{0,k_t}(a_{t+1}, \Omega_{t+1})\right] \\ &+ \beta\lambda_{ck_t}E\max_{N_{t+1}}\Big[g_{t+1}^{1-\gamma}v_{t+1}^{0,k_t}(a_{t+1}, \Omega_{t+1}), \\ &\qquad g_{t+1}^{1-\gamma}v_{t+1}^{1,k_t}(a_{t+1}, \Omega_{t+1})\Big] \\ &+ \beta\sum_{k'\neq k}\lambda_{k_t k'}E\max_{N_{t+1}}\Big[g_{t+1}^{1-\gamma}v_{t+1}^{0,k_t}(a_{t+1}, \Omega_{t+1}), \\ &\qquad g_{t+1}^{1-\gamma}v_{t+1}^{1,k'}(a_{t+1}, \Omega_{t+1})\Big]\Bigg\}. \end{aligned} \tag{10}$$

In this case, the worker is uncertain about the occupation from which he will draw an offer next period, his match quality if he receives an offer from a new occupation, and the evolution of occupation-wide wage shocks.

Because of the discrete labor supply choice, optimal consumption may not be continuous in assets, and the value functions may not be differentiable. I discuss these complications and how I address them in appendix A. Note that the dimensionality problems that typically affect models of occupation choice, discussed in Keane and Wolpin (1997) and elsewhere, are less troublesome here because of the simplified job search framework. In this model, workers are never choosing among more than two options. Employed workers can stay employed or quit; unemployed workers receive at most one job offer, which they can accept or decline. The full spectrum of expected wages in all occupations appear only in the expected value of unemployment, where they can be approximated with multidimensional Gauss-Hermite quadrature.

III. Data and Parameter Estimates

I estimate the wage dynamics and labor mobility parameters using a two-stage approach. I first estimate the wage parameters using method of moments, then estimate the remaining mobility and match parameters, which cannot be mapped directly to observed data moments, using simulated method of moments (McFadden 1989). In this second stage, I simulate employment histories and wage paths for workers starting in each occupation, using the policy rule described in the previous section and the parameters estimated in the first stage, and search for values of the remaining parameters that best align characteristics of the simulated and observed data.

To estimate the determinants of wages in this model, I need a long panel where I can follow workers across occupations and a wide panel to track fluctuations in average wages by occupation over time. No US data set combines these features. For most of the estimation, I use the 1976–2011 waves of the PSID, which has detailed information on a smaller sample of workers over many years. I estimate occupation-to-occupation transition probabilities and occupation-wide wage shocks using the 1988–2011 CPS, which surveys a large sample of workers each month but keeps respondents in the sample for only 2 years. Table A2 lists the method and data source I use for each estimated parameter.

Table A3 describes the two samples. In both data sets, my sample includes men between the ages of 22 and 55 who are not currently in the armed forces or enrolled in school. On average, I observe each worker in the PSID sample for 7.2 working years, during which they work in 2.2 occupations. I further restrict the sample to workers with at least some college education, on the theory that the menu of possible occupations is likely to differ for workers with and without postsecondary education and that a model of substantial investment in occupation-specific skills is particularly relevant for this more educated group. Throughout, I estimate wage dynamics using reported weekly earnings, which adjusts for part-year workers without introducing measurement error from imputing hours for salaried workers. With a slight abuse of terminology I will refer to this measure as the weekly wage to distinguish it conceptually from lifetime earnings.[10] Appendix B describes both data sets and variable definitions in more detail.

A. Occupation-Wide Wage Shocks

The CPS interviews a household for four consecutive months and then again in the same four calendar months a year later. Every month respondents are asked about their employment status and current or most recent occupation. I use these monthly reports to calibrate occupation-by-occupation job offer arrival rates. Employed respondents giving their fourth or eighth interviews are also asked about their usual weekly wage in their current job. I use these outgoing rotation group interviews in each month from January 1988 to December 2011 to estimate the parameters describing the movements of the occupation-wide stochastic component ε_{kt}. To reduce noise from small samples, I pool these monthly responses into quarters (January–March, April–June, etc.).[11]

Without a meaningful panel dimension in the CPS, I cannot control for worker fixed effects or measure occupation tenure. However, it is possible to consistently estimate ρ_k and σ^2_{ke} despite these shortcomings as long as average worker characteristics remain stable over time within each occupation. I begin by regressing log weekly wages on a quadratic of potential experience and indicators for current occupation, race/ethnicity, region of the United States, living in a rural area, and having less than a bachelor's degree.[12] I then calculate the mean residual from this regression in each occupation-quarter cell:

[10] Most prime-age, college-educated men work full time when they are working. In my PSID sample, the median hours worked per week is 44; less than 3% of the sample work fewer than 30 hours per week.

[11] Seven occupations in the CPS sample and 11 occupations in the PSID sample have statistically significant growth in the number of observations over the sample period after controlling for growth in the total sample size. In the CPS sample, computer occupations experience the largest growth, from 224 observations in the first 3 months of 1988 to 444 observations in the last 3 months of 2011. In the PSID sample, sales occupations show the biggest growth in observations, from 45 observations in 1976 to 172 observations in 2011. None of the negative time trends in occupation size are statistically significant. The largest decline over the CPS sample period came in manufacturing occupations (from 644 to 441 observations). In the PSID sample, the largest decline is in management (from 184 to 178 observations).

[12] Under the stability assumption, it is not necessary to control for any worker characteristics, but this step is useful for precision in a finite sample.

$$\bar{w}_{kt} = \bar{\eta}_{kt} + \mu_k + \bar{\alpha}_{kt} + \varepsilon_{kt} + \bar{\zeta}_{kt} + \bar{\xi}_{kt}, \tag{11}$$

where $\bar{\alpha}_{kt}$ indicates the average match quality for workers in occupation k at quarter t. I seasonally adjust the mean residuals by regressing them on a set of quarterly dummies because these seasonal movements are predictable and therefore contribute to variability but not risk. These adjusted mean wage residuals in each quarter are plotted for each occupation in figure A1.[13]

Under the assumption of stability, $\{\bar{\eta}_{kt}, \bar{\alpha}_{kt}, \bar{\zeta}_{kt}, \bar{\xi}_{kt}\} = \{\bar{\eta}_k, \bar{\alpha}_k, \bar{\zeta}_k, \bar{\xi}_k\}$. In this case, the variance and persistence of quarterly occupation-wide shocks are identified by the moments

$$\begin{aligned} \mathrm{var}(\bar{w}_{kt+1} - \bar{w}_{kt}) &= \frac{2\sigma_{ke}^2}{1 + \rho_k}, \\ \mathrm{cov}(\bar{w}_{kt+1}, \bar{w}_{kt}) &= \rho_k. \end{aligned} \tag{12}$$

Because of the CPS sampling process, $\bar{w}_{kt+1}$ and $\bar{w}_{kt}$ are estimated from different samples of workers, so the assumption that average wages in adjacent quarters are correlated only through ρ_k is less troublesome than it would be in a panel data set. As shown in table 1, the average occupation shock has a standard deviation of 0.037 and a half-life of a bit less than 2 quarters.

B. Deterministic Wage Components

Because the PSID interviews the same respondents year after year, I am able to build a detailed work history and measure actual total labor market experience and occupational tenure for each respondent in each year. Measured occupation tenure from surveys can be noisy. From year to year, the respondent may use slightly different words to describe the same job, or occupation coders may assign different codes to the same description, resulting in more changes in occupation codes than there are actual job changes. I use the method developed by Kambourov and Manovskii (2013) to reduce measurement error in occupation changes by considering only changes in occupation codes that coincide with reported employer and position changes. I then assign each job spell the modal occupation coded during that spell.

I estimate equation (1) using the PSID data and including worker fixed effects. The occupation-specific intercepts, μ_k, are therefore identified by workers who move between occupations. I set $\phi(x_{it}, s_{it}) = \phi_1 x_{it} + \phi_2 s_{it} + \phi_3 s_{it}^2$ and $\psi_k(\tau_{ikt}) = \psi_{1k}\tau_{ikt} + \psi_{2k}\tau_{ikt}^2$. Ordinary least squares (OLS) estimates of the returns to tenure will be biased upward by selection. Workers with a better

[13] The ranking of occupations by mean earnings is quite stable over the sample period. Only four occupations exhibit a statistically significant time trend in mean wages after controlling for the trend in mean wages for all workers with some college. The largest of these, for health professionals, represents an average excess wage growth of 0.3% per quarter.

Table 1
Stochastic Wage Components

	ρ_k	σ_{ke}	σ_{ku}	$\sigma_{k\xi}$
Agriculture	.42	.056	.119	.398
	(.103)	(.005)	(.048)	(.097)
Community	.488	.045	.038	.168
	(.087)	(.004)	(.004)	(.011)
Computers	.803	.031	.033	.115
	(.043)	(.003)	(.003)	(.005)
Construction	.755	.032	.049	.186
	(.056)	(.003)	(.005)	(.009)
Education	.299	.028	.027	.154
	(.108)	(.002)	(.004)	(.008)
Engineering	.74	.023	.039	.108
	(.049)	(.002)	(.003)	(.005)
Entertainment	.297	.05	.037	.18
	(.093)	(.004)	(.006)	(.02)
Financial	.745	.034	.04	.235
	(.049)	(.003)	(.005)	(.069)
Health	.781	.04	.042	.183
	(.051)	(.004)	(.004)	(.011)
Legal	.597	.058	.05	.168
	(.093)	(.005)	(.005)	(.014)
Maintenance	.294	.055	.044	.162
	(.081)	(.005)	(.004)	(.018)
Management	.891	.022	.05	.172
	(.02)	(.002)	(.005)	(.014)
Manufacturing	.687	.023	.037	.145
	(.065)	(.002)	(.003)	(.005)
Mechanics	.789	.025	.04	.144
	(.05)	(.002)	(.003)	(.007)
Office support	.634	.03	.033	.14
	(.067)	(.003)	(.003)	(.007)
Protection	.561	.039	.035	.138
	(.076)	(.003)	(.003)	(.007)
Sales	.831	.026	.036	.179
	(.043)	(.003)	(.004)	(.008)
Sciences	.629	.051	.044	.135
	(.061)	(.004)	(.004)	(.01)
Transportation	.485	.043	.048	.151
	(.077)	(.004)	(.004)	(.01)
Cross-occupation average	.617	.037	.044	.172
Observations	753,215	753,215	31,076	31,076

SOURCE.—Current Population Survey and Panel Study of Income Dynamics.

NOTE.—Block-bootstrapped standard errors from 200 replications are shown in parentheses. Cross-occupation average is the observation-weighted average across occupations. Columns are the persistence and variance of occupation-wide wage shocks and the variance of the permanent and transitory idiosyncratic wage shocks. The sample size for σ_{ku} and $\sigma_{k\xi}$ are slightly smaller than the samples for the deterministic wage components because they rely on being able to link residual wages in two adjacent years.

match value are less likely to leave, so workers with 10 years of occupation tenure will have higher average α than workers with 1 year of tenure. Furthermore, workers are more likely to remain in occupations with favorable wage shocks, ε_{kt}, although this selection problem is less severe because of the short half-life of these shocks. I follow Altonji and Williams (2005) and instrument occupation tenure in year t with its deviation from an individual's mean tenure in that occupation, which accounts for selection on α_{ik} but not on ε_{kt}.[14]

The effects of age, experience, and tenure on wages are presented in table 2. On average, 27-year-old workers earn 12% more than 22-year-old workers. Each year of work experience raises wages in any occupation by just under 4%. The estimated effects of age and general experience are high relative to the effects of occupation tenure, suggesting that much of the human capital that these college-educated workers accumulate while working is general. The first 5 years of occupation-specific tenure on average raise wages by 4.2% across occupations, but there is considerable variation around this average. Workers with 5 years of tenure in health occupations earn on average 26% more than rookies, while workers in mechanics and construction receive negative returns to tenure (wages still rise over time in these occupations, just at a lower rate than is implied by the cross-occupation returns to experience and age).

The first column of table 2 presents the estimates of the occupation fixed effects from this wage regression. Average starting weekly wages in 2010 dollars are \$529 (\$27,500 for a full year) for this college-educated sample. Starting wages vary in largely predictable ways across occupations. Lawyers and judges on average earn the most, starting at \$715 per week, while workers starting in agriculture earn only \$431 per week.

C. Idiosyncratic Wage Shocks

I use the residual from the PSID wage regression to identify the variance of permanent and transitory individual shocks. The residual from this PSID log wage regression comprises

$$w_{ikt} = \alpha_{ik} + \varepsilon_{kt} + \zeta_{it} + \xi_{it}. \tag{13}$$

There are not enough observations in each occupation–time period cell in the PSID to reestimate the parameters governing the occupation shocks,

[14] Tables A4 and A5 present estimates from three simpler specifications that do not instrument for occupation tenure: OLS including only occupation indicators, age, experience, and tenure; then adding additional observed worker characteristics; and finally adding individual fixed effects. Estimated returns to occupation tenure fall with each additional level of controls, with the largest decline between the estimation with individual fixed effects to the preferred specification with both fixed effects and instruments for tenure.

Table 2
Deterministic Wage Components

	μ_k	Effect of Age, Experience, and Tenure: Years/10	(Years/10)^2	Effect of 5 Years
Age − 22		.314	−.137	.123
		(.01)	(.001)	(.005)
Total experience		.392		.196
		(.01)		(.005)
Agriculture	6.067	.042	−.009	.019
	(.01)	(.014)	(.004)	(.007)
Community	6.133	.12	.012	.063
	(.008)	(.014)	(.006)	(.007)
Computers	6.254	.159	−.026	.073
	(.006)	(.009)	(.004)	(.005)
Construction	6.288	−.263	.087	−.11
	(.006)	(.01)	(.004)	(.005)
Education	6.215	.249	−.07	.107
	(.006)	(.009)	(.003)	(.005)
Engineering	6.378	−.031	.032	−.008
	(.005)	(.007)	(.003)	(.004)
Entertainment	6.167	.243	−.051	.109
	(.007)	(.014)	(.006)	(.007)
Financial	6.28	.127	−.044	.052
	(.005)	(.009)	(.003)	(.004)
Health	6.436	.597	−.157	.259
	(.008)	(.01)	(.004)	(.005)
Legal	6.563	.449	−.094	.201
	(.012)	(.015)	(.006)	(.007)
Maintenance	6.111	−.055	−.044	−.039
	(.01)	(.028)	(.013)	(.014)
Management	6.34	.065	.015	.036
	(.0004)	(.005)	(.002)	(.002)
Manufacturing	6.44	−.161	.022	−.075
	(.005)	(.008)	(.003)	(.004)
Mechanics	6.28	−.178	.033	−.081
	(.006)	(.01)	(.003)	(.005)
Office support	6.222	−.067	.005	−.032
	(.005)	(.01)	(.004)	(.005)
Protection	6.268	.092	−.015	.042
	(.007)	(.011)	(.005)	(.006)
Sales	6.204	.204	−.086	.081
	(.004)	(.007)	(.003)	(.004)
Sciences	6.329	.068	−.004	.033
	(.007)	(.012)	(.005)	(.006)
Transportation	6.194	.148	−.045	.063
	(.006)	(.013)	(.005)	(.006)
Cross-occupation average	6.272	.095	−.023	.042
Observations	40,073	40,073	40,073	40,073

SOURCE.—Panel Study of Income Dynamics.
NOTE.—Standard errors are shown in parentheses. The last three columns describe the effect on log weekly wages of years of age, total labor experience, and occupation tenure.

ε_{kt}, along with the remaining parameters. Instead, I estimate the variance of permanent, $\sigma^2_{k\xi}$, and transitory, $\sigma^2_{k\xi}$, wage shocks using moments of this residual for workers who remain in the same occupation and adjust for the expected contribution of the evolution of the occupation shock using the estimates of ρ_k and σ^2_{ke} from the previous section. I estimate the remaining shock parameters with the generalized method of moments using the overidentified set of moments:

$$\begin{aligned}
\mathrm{var}(w_{ikt+1}) - \mathrm{cov}(w_{ikt}, w_{ikt+1}) &= (1 + \rho_k^2)\sigma^2_{ke} + 4\sigma^2_{ku} + \sigma^2_{k\xi}, \\
\mathrm{cov}(w_{ikt}, w_{ikt+1}) - \mathrm{cov}(w_{ikt-1}, w_{ikt}) &= 4\sigma^2_{ku}, \\
\mathrm{var}(w_{ikt+1} - w_{ikt}) &= 2(1 + \rho_k^2)\sigma^2_{ke} + 4\sigma^2_{ku} + 2\sigma^2_{k\xi}, \\
\mathrm{cov}(w_{ikt+1} - w_{ikt}, w_{ikt} - w_{ikt-1}) &= (\rho_k^4 + \rho_k^6 - \rho_k^2 - 1)\sigma^2_{ke} - \sigma^2_{k\xi}.
\end{aligned} \tag{14}$$

These moments take into account that I observe wages only once a year in the PSID but that wage shocks occur quarterly.[15] The parameters estimated from the PSID wage residuals are presented in table 1. Heathcote, Perri, and Violante (2010) point out that moments in levels and differences generate different estimates of the relative size of permanent and transitory shocks. These estimates from the combination of moments are consistent with the growth in cross-sectional wage variance with age in the PSID, as I discuss in Section III.F.

On average, the semipersistent occupation-wide shock and the permanent idiosyncratic shock contribute about the same amount of uncertainty to wage growth in each quarter. However, the permanent shock has a larger influence on lifetime wage uncertainty because the shocks build on one another rather than reverting to the mean. Overall, workers in education occupations face the lowest wage risk, with a standard deviation of the occupation-wide shock of 0.028, low persistence of this shock, and a permanent shock standard deviation of 0.027. Agricultural workers face by far the greatest wage risk. Almost half of agricultural workers in the PSID are self-employed, compared with less than 10% in all other occupation categories except law (25%), which also exhibits fairly high wage risk. To illustrate this variation in risk, figure 1 plots two sample simulated wage paths for workers in education and agriculture. These simulations, using the wage parameter estimates in tables 1 and 2, assume that workers remain employed in the same occupation for 120 quarters.[16]

[15] From 1999 onward, when the PSID is asked biannually, I adapt these moments to reflect 2-year changes in wages.

[16] These simulations are described in more detail in Sec. IV.

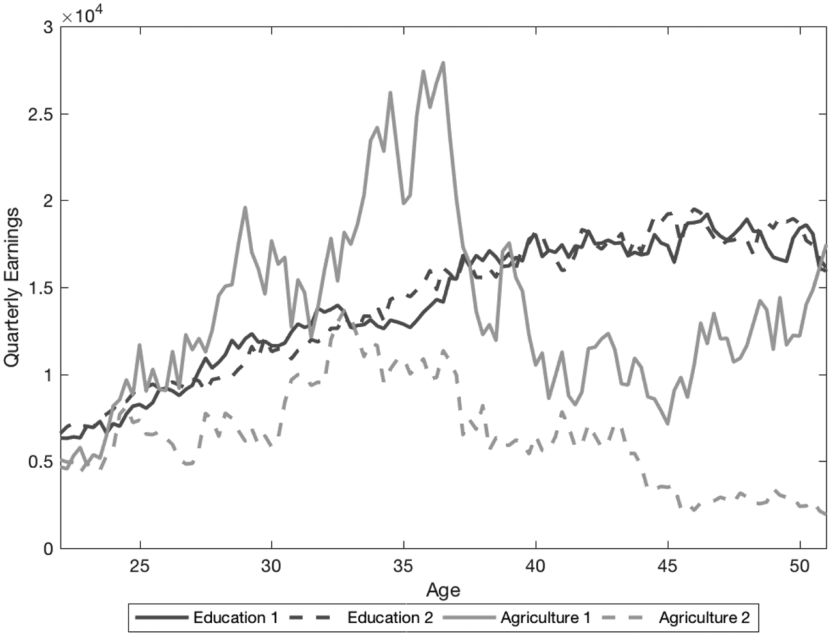

FIG. 1.—Sample high-risk and low-risk wage paths. This figure plots quarterly earnings over the life cycle for two simulated workers in education (the occupation with the lowest wage risk) and two in agriculture (the occupation with the highest wage risk). These simulations use the wage parameters in tables 1 and 2 and assume that workers remain employed in the same occupation in all periods. They are described in more detail in Section IV.B. A color version of this figure is available online.

D. Labor Mobility

I estimate the exogenous job destruction rate, the current-occupation and new-occupation offer arrival rates, and the variance of occupation match quality using simulated method of moments. I provide the details of this step in appendix C. I simulate 30 years of earnings and employment moves for 500 workers starting in each occupation. I generate a lifetime of shocks for each worker, then simulate working lives using the policy rule described in Section II.D to guide workers through the shocks they encounter. I then compare the characteristics of these simulated data to the characteristics of observed data and update my guess of the remaining parameters until the characteristics of the simulated and observed data align. To match the real and simulated data, I assume that simulated workers begin working at age 22. Estimating a K-by-K matrix of offer arrival rates is not feasible within the simulated method of moments estimation. Instead, I estimate the probability that an unemployed worker receives an offer from any new occupation and calibrate the share of new offers from each occupation, conditional on receiving an outside offer.

The data characteristics I target are the average duration of completed unemployment spells by last occupation, the running average occupation tenure of employed workers by occupation and age bracket, the annual probability of changing occupations by starting occupation and age bracket, and the variance of wage changes around occupation moves, all measured from the PSID. I do not observe enough unemployment spells to match unemployment duration separately by age bracket as well as occupation. In theory, average unemployment duration could increase with age as workers with more tenure in their current occupation wait longer for an offer in that same occupation, but this effect does not show up strongly in the PSID data. Many workers remain in the same occupation for all the years I observe them in the PSID, so looking at the length of completed spells rather than average tenure would both reduce my observations and understate the persistence of workers in occupations.

Table 3 presents these mobility and match parameters. On average, employed workers face a 3.6% chance of having their job destroyed each quarter. This employment risk is somewhat negatively correlated with wage risk. For example, agricultural workers have one of the lowest risks of losing their jobs, but they have high wage risk. Unemployed workers on average face a 35% chance of receiving a job offer from their current occupation and a 33% chance of receiving an offer from any other occupation. Because these two possibilities are mutually exclusive, these estimates imply that each quarter most unemployed workers will receive some job offer.

The standard deviation in worker-occupation match is quite large. Workers have a 22% probability of earning either 60% less or 60% more than their average wage in different occupations. Observed match variability is considerably lower because workers will generally not accept jobs with which they are a very bad match. In the simulations, workers accept only 24% of job offers that involve an occupation change, and accepted offers have higher average match components. Low, Meghir, and Pistaferri (2010) include a job search process similar to mine with match quality that varies with job rather than occupation. Their estimated job destruction and arrival rates are similar to my cross-occupation averages. They estimate a standard deviation of match quality of 0.228, substantially lower than mine, which makes sense since they are considering changes in match within occupations as well as between them.[17]

E. Calibrated Parameters

I set the quarterly discount rate, β, to 0.987, equivalent to a 0.95 annual rate, and the quarterly risk-free interest rate, r, to 0.5%, a 2% annual rate.

[17] The difference may also partially stem from different estimation methods, as they estimate the variance of match quality from observed wage changes, which includes only the offers that workers accept, with controls for selection.

Table 3
Occupation Mobility and Match

	δ_k	λ_{ck}	λ_{nk}	σ_α
Agriculture	.019	.236	.452	
	(.002)	(.028)	(.054)	
Community	.039	.192	.181	
	(.005)	(.029)	(.043)	
Computers	.043	.561	.182	
	(.012)	(.039)	(.021)	
Construction	.044	.447	.356	
	(.011)	(.043)	(.035)	
Education	.029	.503	.397	
	(.013)	(.073)	(.079)	
Engineering	.033	.478	.253	
	(.004)	(.039)	(.036)	
Entertainment	.04	.477	.28	
	(.006)	(.069)	(.073)	
Financial	.033	.379	.346	
	(.007)	(.05)	(.06)	
Health	.042	.287	.067	
	(.009)	(.015)	(.022)	
Legal	.037	.317	.081	
	(.007)	(.022)	(.07)	
Maintenance	.052	.141	.391	
	(.036)	(.04)	(.076)	
Management	.032	.481	.374	
	(.003)	(.036)	(.032)	
Manufacturing	.033	.34	.47	
	(.005)	(.038)	(.048)	
Mechanics	.029	.311	.353	
	(.008)	(.035)	(.072)	
Office support	.035	.211	.462	
	(.009)	(.018)	(.091)	
Protection	.032	.32	.308	
	(.026)	(.057)	(.067)	
Sales	.046	.345	.353	
	(.008)	(.052)	(.081)	
Sciences	.032	.418	.518	
	(.012)	(.053)	(.075)	
Transportation	.041	.222	.35	
	(.004)	(.015)	(.029)	
Cross-occupation average	.036	.351	.325	.609
				(.011)

NOTE.—Standard errors are shown in parentheses. Columns are quarterly exogenous job destruction rates, quarterly offer arrival rates from current and new occupations, and the variance of worker-occupation match.

I assume that workers receive $pen = 0.3$ share of their period T earnings during retirement (Mitchell and Phillips 2006), which helps discipline asset accumulation in the model. I also assume that workers receive $b = 0.2$ share of their earnings in their last occupation during unemployment spells. Meyer (2002) finds that 40% of unemployed workers receive unemployment insurance benefits and those that receive them get on average 50% of their most recent wages, yielding an expected replacement ratio of 20%. I set the coefficient of relative risk aversion, γ, to 1.5, taken from Attanasio and Weber (1995). Finally, I set the transition matrix for workers who receive a job offer from a new occupation, $\lambda_{kk'}$, to the observed distribution of quarterly occupation to occupation moves in the CPS (i.e., occupation changes between the first and fourth interviews or between the fifth and eight interviews).

F. Model Fit

Table 4 assesses how well these simulations fit the average targeted characteristics of observed data. Table A6 presents all matched moments. The simulations do a good job of matching average occupation tenure by age. The simulated workers have longer average unemployment spells, which partially reflects the simplifying but inaccurate assumption that workers receive at most one job offer per quarter.

The simulations match the sharp decline in the probability of occupation changes with age, although this decline is steeper in the simulations than in the data. Two features of the model contribute to this gap. First, the model abstracts from any concept of heterogeneous jobs within the same occupation. Observed workers could search out better job matches within their current occupation or look in a new occupation, but the simulated workers can improve their match quality only by changing occupations. Second, real workers care about match along other dimensions of an occupation that I do not model. Workers in the data may remain in a low-paying but satisfying field early in life or leave a well-paying occupation later in life to pursue other interests, but my simulated workers will not.[18] This pattern is borne out in table A6, where low-paying and risky occupations like maintenance work have particularly high rates of occupation changes. The correlation between the observed and simulated occupation changes across occupations are strongly positive, indicating that the model matches differences in the frequency of moves across starting occupations. Finally, the simula-

[18] While adding these kinds of nonpecuniary preferences would improve the model's ability to match observed data, it would also muddy the interpretation of the lifetime risk estimates. As modeled, the simulations represent the best that consumption-loving, risk-averse workers can expect to do by starting in each occupation. The variance of lifetime earnings across different simulated workers with heterogeneous preferences for particular occupations would be harder to interpret.

Table 4
Fit for Simulated Method of Moments Matched Moments

	Average Moment from Data	Average Moment from Simulations
Duration of unemployment:		
All ages	1.37	4.71
Average occupation tenure:		
Age 22–27	8.50	7.19
Age 28–41	27.68	27.03
Age 42–51	57.19	56.72
Pr(change occupation):		
Age 22–27	.137	.242
Age 28–41	.062	.053
Age 42–51	.041	.016
Sd(wage change with occupation move):		
1-year change	.198	.251
2-year change	.245	.230

NOTE.—The first three sets of moments are matched separately by occupation. This table reports the average statistics across all occupations in the real and simulated data. Table A6 reports the occupation-specific moments. The variance of wage changes during occupation moves is calculated across all occupations. The variances of 1- and 2-year wage changes from the Panel Study of Income Dynamics data are calculated using 269 and 1,228 observations, respectively. Observation counts for the other moments are reported in table A6. Duration of unemployment and average tenure are measured in quarters. Probability of occupation change is measured over a year, conditional on being employed at the end of the year.

tions match the average variance of wage changes when workers move to a new occupation, which pins down the variance of match quality.[19]

Figure 2 plots the evolution of mean earnings over the life cycle in the simulated data and in the PSID. Figure 3 does the same for the cross-sectional variance of earnings. The evolution of earnings over the life cycle reflects the combination of deterministic wage growth, wage shocks, and the interaction of these exogenous developments with both exogenous and endogenous moves between occupations. Mean earnings rise somewhat more over the life cycle in the simulations than in the data, again reflecting that the simulated workers have no nonpecuniary preferences to slow their pursuit of higher wages. While nothing in the model explicitly targets changes in cross-sectional variance over time, the simulated data align very closely with the observed changes in variance in the PSID. Figures A2 and A3 show these mean and variance plots separately for each occupation. As anticipated, the gap between the mean of observed and simulated earnings is larger in relatively low-paying occupations, such as construction and community and social work; many of the simulated workers who begin in these occupations with bad matches will search for work in other occupations, leaving behind a selected

[19] Changes in wages over the 2 years surrounding an occupation change include more accumulated shocks to the individual random walk component than changes in wages over 1 year. In the simulations, the small implied difference ($4\sigma^2_{ku} = 0.0144$ on average) is overcome by sampling variation.

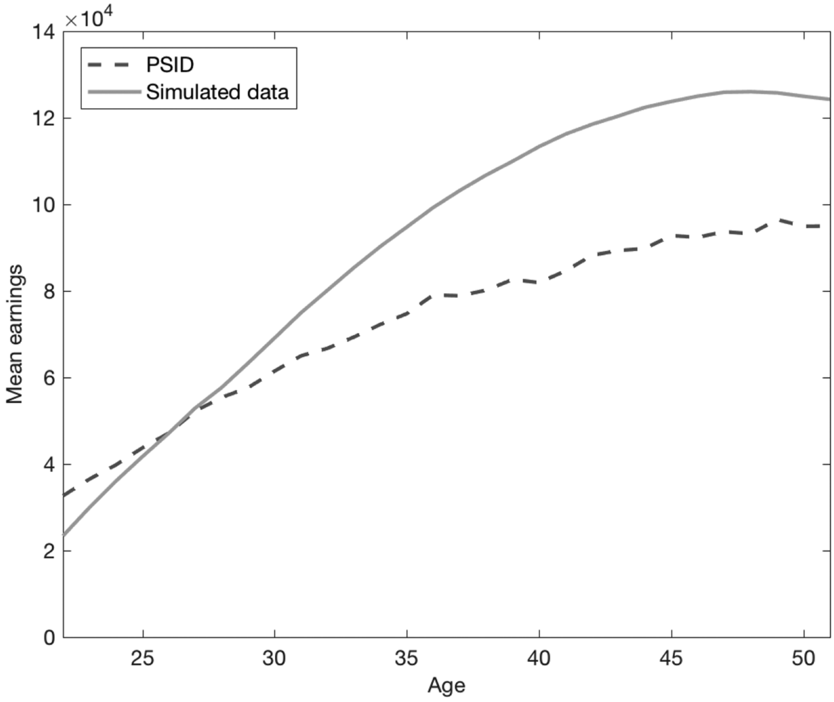

FIG. 2.—Cross-sectional mean of observed and simulated earnings. This figure plots the mean annual earnings in the Panel Study of Income Dynamics (PSID) by age and the mean of simulated annual (sum of 4 quarters) earnings for simulated workers. A color version of this figure is available online.

sample. Nonetheless, the ranking of high- and low-earning and high- and low-risk occupations is similar across the simulated and real data. At age 40, the correlation across occupations of mean real and simulated earnings is 0.60, while the correlation in cross-sectional variance is 0.61.

Figure 4 considers the sources of wage growth over the life cycle. Because I rarely observe complete life-cycle earnings for the participants in the PSID, I cannot compare this decomposition directly with the data. However, these decompositions are broadly in line with earlier studies. Topel and Ward (1992) find that on average men hold seven jobs during the first 10 years of their career, about two-thirds of the total jobs they will hold. The simulated workers in this model on average work in 2.14 occupations during their first 10 years, 85% of the average total numbers of occupations they will sample. Together, these statistics suggest that the decline in occupational mobility over age is even steeper than the decline in job mobility, which confirms the importance of occupation-specific as well as job-specific skills.

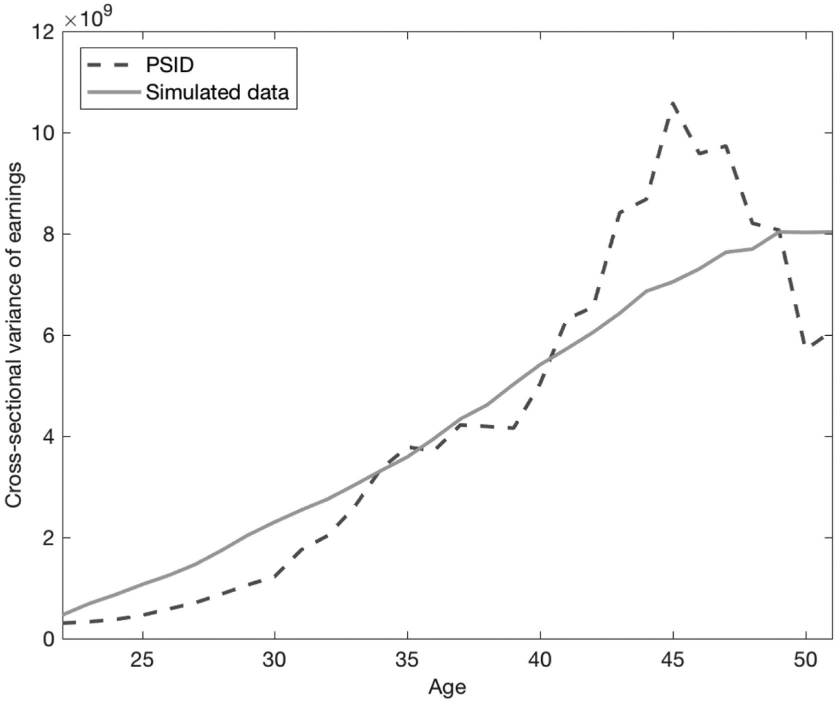

FIG. 3.—Cross-sectional variance of observed and simulated earnings. This figure plots the raw cross-sectional variance of annual earnings in the Panel Study of Income Dynamics (PSID) by age and the cross-sectional variance of simulated annual (sum of 4 quarters) earnings for simulated workers. A color version of this figure is available online.

On average, 55% of wage growth over the full working lives of these simulated workers is generated by moves between occupations. Another 38%, on average, is generated by the returns to age and accumulated total work experience, while the final 7% is due to accumulated occupation tenure. Topel and Ward (1992) estimate that at least 33% of observed wage growth for young men can be attributed to moves between jobs. Again, the stronger role for occupational mobility in these simulations likely reflects the lack of preferences for particular occupations. It may also reflect the purely random allocation of workers to starting occupations. Some of these initial matches will be quite low productivity. In reality, workers may already have some sense of their comparative advantage before starting work and choose their first jobs accordingly. Sorting between occupations in the simulations resolves very quickly. As shown in figure 4*B*, moves between occupations on average account for only 31% of wage growth from the third year of work to the last.

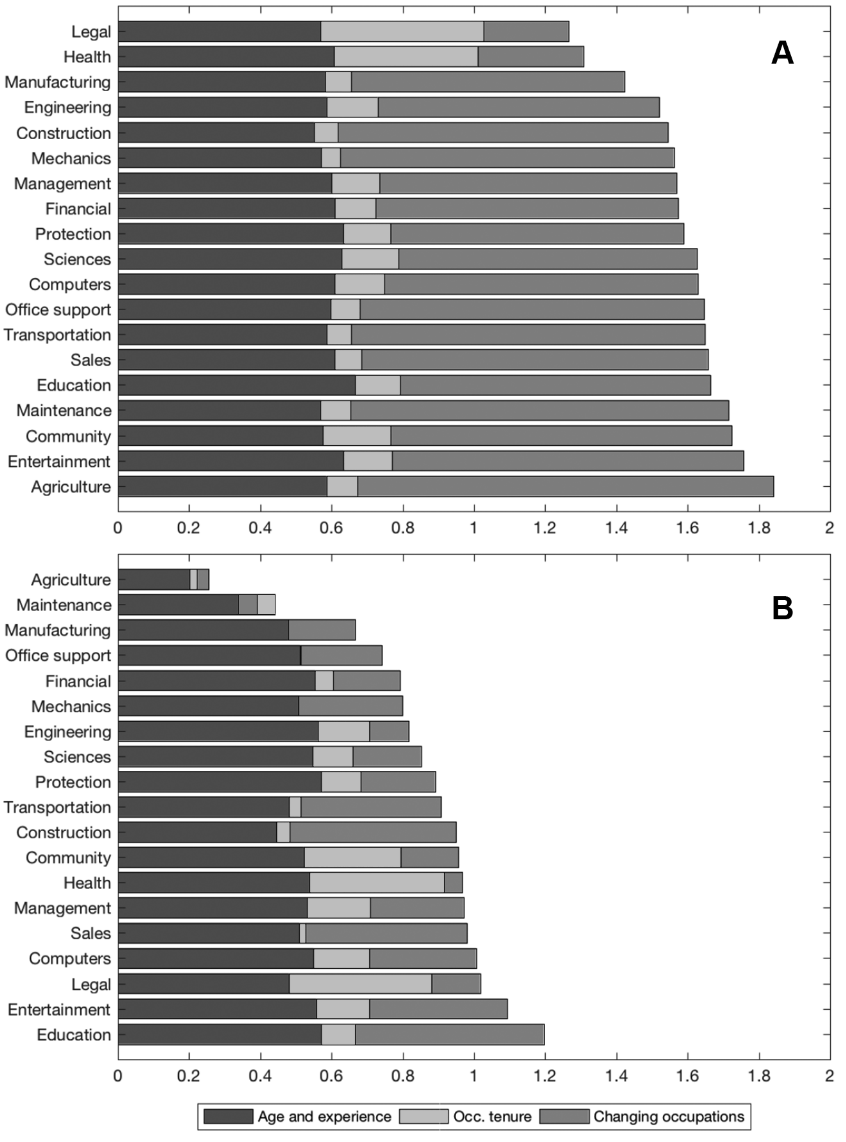

FIG. 4.—Sources of life-cycle wage growth. *A*, Over full working life. *B*, From year 3 to the end of working life. The graphs plot the average components of the change in log wages over the life cycle of simulated workers in the baseline model. Wage growth is attributed to returns to age and experience (this category also includes a very small contribution from the average change in wage shocks), returns to occupation-specific tenure, and growth from moving between occupations (which includes moves to occupations with higher mean base wages and to occupations with better idiosyncratic match quality). A color version of this figure is available online.

G. Unmodeled Sources of Heterogeneity

Like earlier studies exploring risk-return trade-offs across occupations, this paper assumes that the riskiness of occupations remains constant over time. This formulation captures fixed differences in the riskiness of earnings across careers, for example, varying degrees of procyclicality or greater differences between individual success and failure. It does not capture the risk of a permanent change in occupation demand due to technological change. If this sort of technological shock is unforeseeable, then it represents a kind of unknown risk for which workers will not demand compensation. I explore the effect of unanticipated wage shocks in Section V. However, if riskiness evolves gradually over time, as in Meghir and Pistaferri (2004), then younger workers entering an occupation will have different expectations of risk—and require different compensation—than older workers who entered under different circumstances. These estimates would then give an average of both the riskiness and the expected earnings over the sample period.

The uncertainty about mean wage changes generated by business cycle fluctuations will be captured as part of the variance of occupation-wide shocks, ε_{tk}. However, other determinants of wages and job mobility, such as job destruction and offer arrival rates, may also fluctuate over the business cycle in ways that I do not model. The size of the PSID sample precludes estimating most of these parameters separately in booms and recessions. The parameters estimated using all years of data represent the averages of these factors over booms and recessions, an approximation of the average labor market conditions workers can expect to face over their working lives. As discussed in appendix D, including recession indicators in the wage equation has modest effects, of the expected signs, on the estimated occupation fixed effects and shock variances.[20]

Blundell, Graber, and Mogstad (2015) find that the variance of income shocks falls over the life cycle. Their estimated income shocks include the effects of unemployment and job changes, so some of this decline is captured endogenously in this model as moves between occupations fall with age. Appendix D discusses estimates of the wage shocks separately for older and younger workers. The standard deviation of the individual permanent shock falls slightly with age for most occupations, from an average of 0.044 to an average of 0.039. These declines are small relative to differences across occupations, so assigning a common shock to workers of all ages is unlikely to substantially change the results. The estimated variance of the occupation-wide shocks does not fall systematically with age, consistent with the interpretation that this shock captures broader changes in productivity and demand.

[20] As pointed out by Storesletten, Telmer, and Yaron (2004) and others, the variance of wage shocks may also fluctuate over the business cycle. Accounting for this variation is, however, beyond the scope of this paper.

IV. Lifetime Earnings Risk

When workers choose a career path, they consider the overall riskiness of earnings in that field, combining wage risk, employment risk, and occupational mobility. To calculate the expected value of lifetime earnings in a given career and the variance around that expectation, I simulate earnings streams for 1,000 workers starting in each occupation. I then calculate the discounted stream of realized earnings for each simulated worker and take the mean and variance of these discounted lifetime earnings for workers starting in each occupation. While in reality all workers in the same occupation experience the same sequence of occupation-wide shocks, in this exercise each worker faces a different sequence of occupation shocks to capture that element of wage uncertainty.

While I control for individual fixed effects in my estimation, I do not simulate any ex ante heterogeneity, although workers become heterogeneous as soon as they draw their first wage shocks. Nor do workers have preferences for certain kinds of work beyond uniform risk aversion. The variance of these simulated lifetime earnings streams therefore represents the total earnings uncertainty associated with beginning in a given occupation, taking into account that workers will optimally respond to the shocks they experience by accepting new job offers and perhaps changing occupations.

Figure 5 plots the mean of lifetime earnings by starting occupation against the ratio of the variance and the mean of lifetime earnings in each occupation.[21] Workers who begin in legal occupations, the best-paid group, can expect to earn about 15% more over their lives than workers who begin in community and social service occupations, the lowest-paid group. However, the variation in realized lifetime earnings for individuals dwarfs the differences in average lifetime earnings across occupations. Twenty-eight percent of workers who begin in community occupations will earn at least $2.1 million over their lives, the average lifetime earnings for workers who begin in law occupations. Likewise, 54% of workers who begin working in law will end up earning less over their lives than the average worker starting in community service.

[21] Lifetime earnings are bounded below by zero and have a long right tail, which creates a mechanical relationship between the mean and the variance. Unemployment shocks and search for better-matched occupations prevent lifetime earnings from being exactly log-normally distributed. Instead, lifetime earnings for workers starting in each occupation will exhibit various degrees of positive skewness depending on the relative importance of unemployment spells (less skewness) and occupation mobility (more skewness) for each group. No single normalization can perfectly correct for skewness in all occupations, but considering the ratio of the variance of lifetime earnings to the mean reduces the mechanical relationship. The variance of log lifetime earnings (plotted in fig. A4), the raw variance of lifetime earnings, and the ratio of the variance to the square of the mean all create similar rankings of riskiness across occupations (correlation more than 0.9).

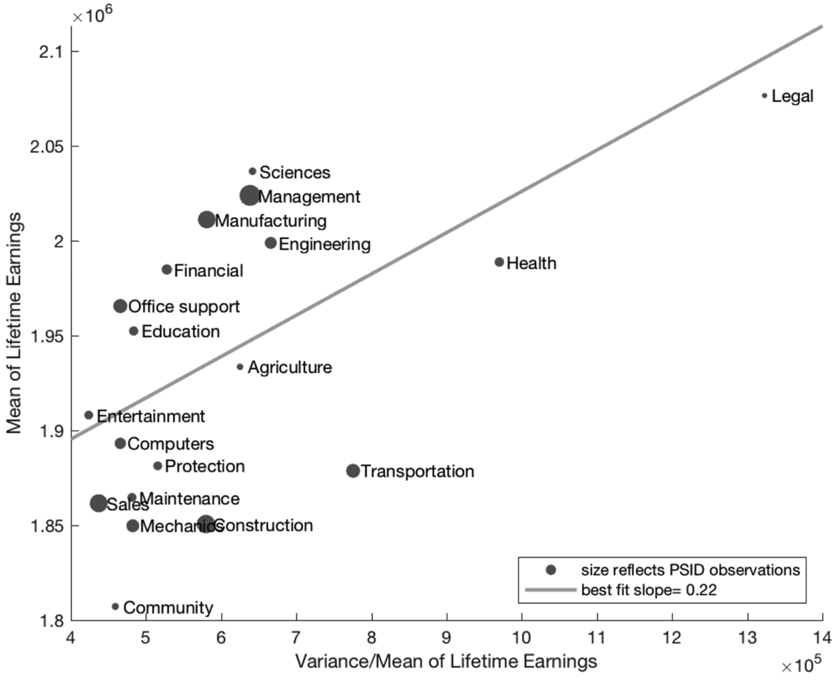

FIG. 5.—Mean and variance of lifetime earnings by starting occupation. This figure plots simulated lifetime earnings streams for workers starting in each occupation, as described in the text. The slope of the risk-return relationship if legal workers are omitted is 0.23. PSID = Panel Study of Income Dynamics. A color version of this figure is available online.

A. Risk Aversion and Occupation Risk Premia

If risk-averse workers are aware of differences in lifetime earnings risk across careers then they should, all else equal, require higher expected lifetime earnings in those careers to compensate for the risk. Workers who are particularly risk averse should also sort into less risky careers. While many other factors also influence average earnings across occupations and occupational sorting, both of these patterns are apparent in the data.

Figure 5 shows a clear positive relationship between the mean of the simulated lifetime earnings streams in each occupation and the ratio of the variance of lifetime earnings to the mean. The estimated slope of the risk-expected return frontier is 0.22. This positive relationship between earnings uncertainty and average earnings reinforces the findings of Campbell (1996) and Jagannathan and Wang (1996) that workers cannot easily insure against labor income risk. If risk-averse workers could buy insurance that guaranteed a steady earnings stream, then they would require only the price of this insurance as additional compensation to make them indifferent between more and less risky earnings streams. My results imply that lawyers would trade 9.3% of their total lifetime earnings (about $8,500 each year) to reduce their lifetime earnings risk to the level faced by sales workers.

In 1996, the PSID asked all male heads of household a battery of questions about the respondent's willingness to accept a series of hypothetical jobs with risky earnings streams. I follow the method of Kimball et al. (2008) to impute individual coefficients of relative risk aversion from these questions. Because individuals tend to get more risk averse as they age, I adjust for age in 1996 in these imputations. I discuss this imputation in more detail in appendix E. The PSID respondents demonstrate a wide range of risk preferences. As shown in table A10, individuals who rejected all of the risky jobs, the most common response, have an average imputed risk aversion of almost 6, while those who accepted all of the risky jobs have an average imputed risk aversion of 1.16.

To assess the degree of sorting into occupations by risk preference, I group workers who answered these risk questions by the occupation of their first observed job and calculate the mean imputed risk aversion in each group. Figure 6 plots this mean risk aversion for workers starting in each occupation against my occupation-specific measure of lifetime earnings risk. The plot shows a loose, negative relationship between the riskiness of an occupation and average risk aversion, the expected pattern if workers are aware of the relative earnings riskiness of occupations but weigh their aversion to risk against other factors, such as tastes and skills for particular types of work, when choosing a starting occupation. The correlation between average imputed risk aversion and lifetime earnings risk is −0.21.

This sorting by risk preference flattens the observed risk-return trade-off plotted in figure 5. The slope of the observed risk-return frontier reflects the risk aversion of the marginal worker who accepts a job at each level of risk. Since the risk tolerance of these marginal workers is increasing in earnings risk, the relationship between the mean and variance of lifetime earnings is flatter than the slope of any single worker's indifference curve. The sorting I find is consistent with the findings of Schulhofer-Wohl (2011), who uses a similar battery of gamble questions to measure risk aversion in the Health and Retirement Survey. He finds that workers who are more risk tolerant have more volatile income and consumption and makes the same point that this sorting affects the interpretation of the risk-return frontier.

B. The Roles of Wage and Employment Risk

The total earnings risk plotted in figure 5 reflects a combination of wage risk, employment risk, and occupational mobility. To understand the relative importance of these various sources of risk, I compare the variance of lifetime earnings simulated from the full model with the variance of simulated lifetime earnings from a simpler model in which workers remain em-

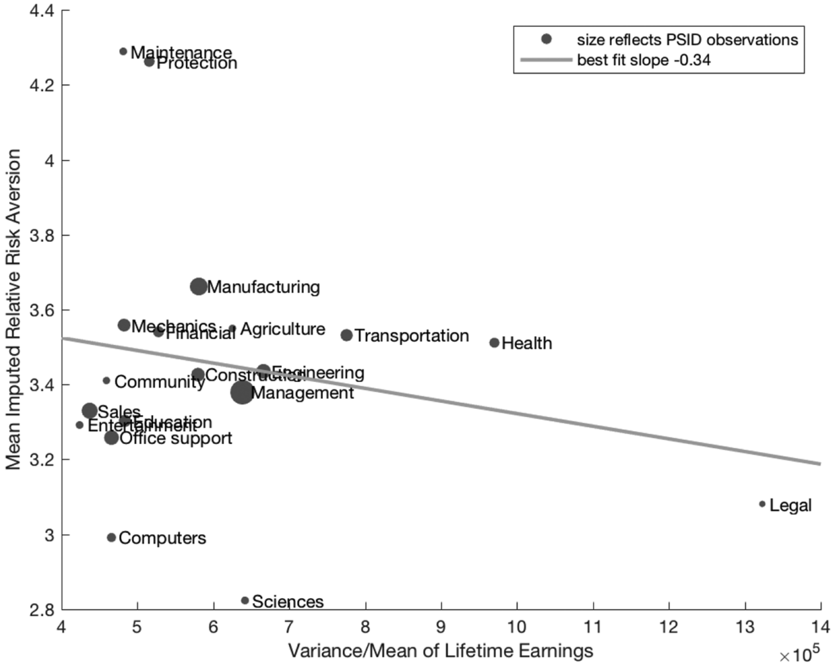

FIG. 6.—Risk aversion and the choice of starting occupation. This figure plots the variance of simulated lifetime earnings streams and average imputed coefficient of relative risk aversion for workers starting in each occupation, as described in the text. PSID = Panel Study of Income Dynamics. A color version of this figure is available online.

ployed in their starting occupation in all periods and face uncertainty only from wage shocks.

Both the mean and the variance of lifetime earnings will differ in these two models. Unemployment spells, where workers earn only 20% of their regular earnings, lower expected lifetime earnings. Because of the skewed distribution of lifetime earnings, lowering the mean will also lower the measured variance. Balancing this effect, surprise job losses add an additional source of risk, raising the variance of lifetime earnings. The option to move between fields also has several competing effects on expected earnings and total risk. The ability to change occupations mitigates other risks by allowing workers to escape some low wage shocks and by providing additional employment opportunities to workers who lose their job. However, workers who change occupations will lose their occupational tenure, lowering earnings and increasing the potential cost of a job loss. Finally, the opportunity to move through occupations searching for a good match raises workers' expected lifetime earnings but also raises lifetime earnings uncertainty.

On balance, mean lifetime earnings are lower with only wage risk for workers who start in all occupations except health and law. These two occupations have particularly low exit rates,[22] so workers who start in these fields do not gain enough from the ability to search to counteract the cost of unemployment spells. The variance of lifetime earnings is substantially lower in the model with only wage risk for workers who start in all occupations except health, law, and agriculture. For law and health, the lower variance in the model with unemployment and mobility is a mechanical result of the lower mean. As shown in table 1 and figure 1, agricultural workers face an unusual degree of wage risk. For workers who start in agriculture, the ability to change occupations and escape these large shocks more than compensates for the added uncertainty of unemployment, leading to lower variance in the full model.

Figure 7 plots the variance-mean ratio of simulated lifetime earnings for each starting occupation in the full model and in the model with only wage risk. This plot illustrates differences in the variance of lifetime earnings after adjusting for the differences in the mean. Workers in only four occupations exhibit higher adjusted variance of lifetime earnings in the full model than in the wage risk model: those in the sciences, maintenance, mechanics, and transportation. For workers starting in law, health, and agriculture, both the raw variance and the adjusted variance of lifetime earnings are lower in the full model. For workers starting in the majority of the remaining occupations, both the mean and the variance of lifetime earnings are higher in the full model, but the variance does not rise by as much as the mean. The additional risk of losing one's job and accumulated tenure is substantially offset by the option to mitigate wage and employment shocks by changing occupations. This escape option creates important differences between the lifetime earnings risk measured in this paper and measures that use only the variance of wage shocks. The next section explores how occupational mobility works to mitigate shocks.

V. Occupation Mobility in Response to Wage Shocks

To illustrate the insurance value of occupational mobility, I simulate earnings streams for workers who experience a permanent occupation-specific wage shock. In this simulation, workers suddenly face lower wages in their current occupation, but their expected wages in any other occupation remain unchanged. This kind of shock is outside the framework of the model of normal wage dynamics, in which workers experience idiosyn-

[22] Workers in these high-paying occupations have less incentive to change sectors. They also receive fewer job offers from new occupations. These offer rate estimates are driven by low observed exit rates, even conditional on earnings, which may reflect preferences and the specialized schooling required for most jobs in these occupations.

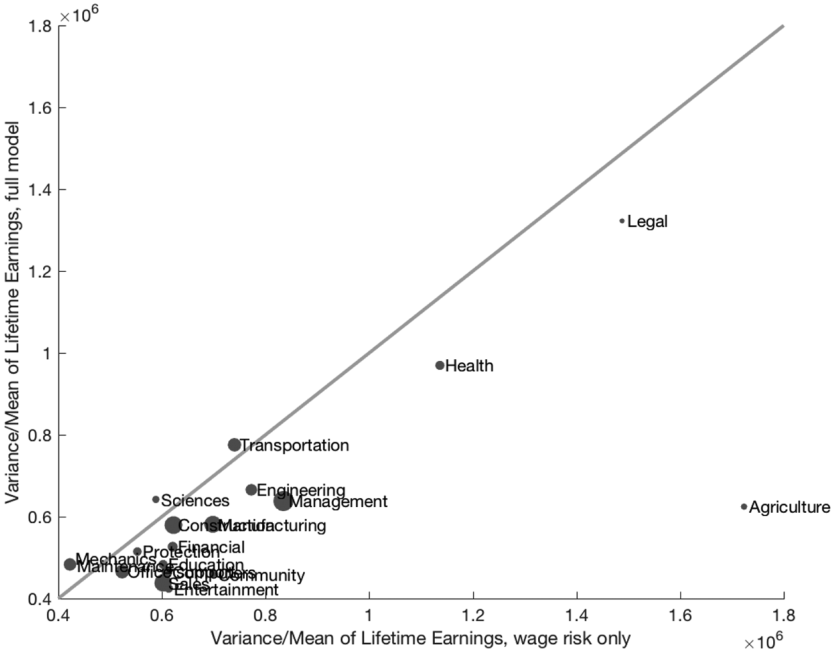

FIG. 7.—Lifetime earnings uncertainty from wage and employment shocks. This figure plots the ratio of the variance of simulated lifetime earnings in each occupation to the mean of these earnings, simulated with and without employment shocks and occupational mobility as described in the text. PSID = Panel Study of Income Dynamics. A color version of this figure is available online.

cratic permanent wage shocks that they carry from one occupation to the next and AR(1) occupation-specific shocks that I estimate to be only moderately persistent.[23] The wage process I estimate from the past 40 years of data can be thought of as encompassing known risks; workers cannot forecast the realizations of their individual shocks, but they do know the probability distribution. These permanent occupation-specific shocks can be thought of as unanticipated risk, for example, occupation-specific effects of technological developments or changes in international competition.

Figure 8 plots the evolution of earnings over the life cycle for workers who experience a 20% drop in wages in their current occupation at different ages. Average earnings fall sharply on impact, usually by more than 20%, because some workers respond to the shock by quitting to look for work

[23] In practice, I implement this permanent occupation-specific shock by lowering the match component of each worker with their current occupation. With this approach, the simulated workers immediately recognize the wage shock as permanent and adjust accordingly.

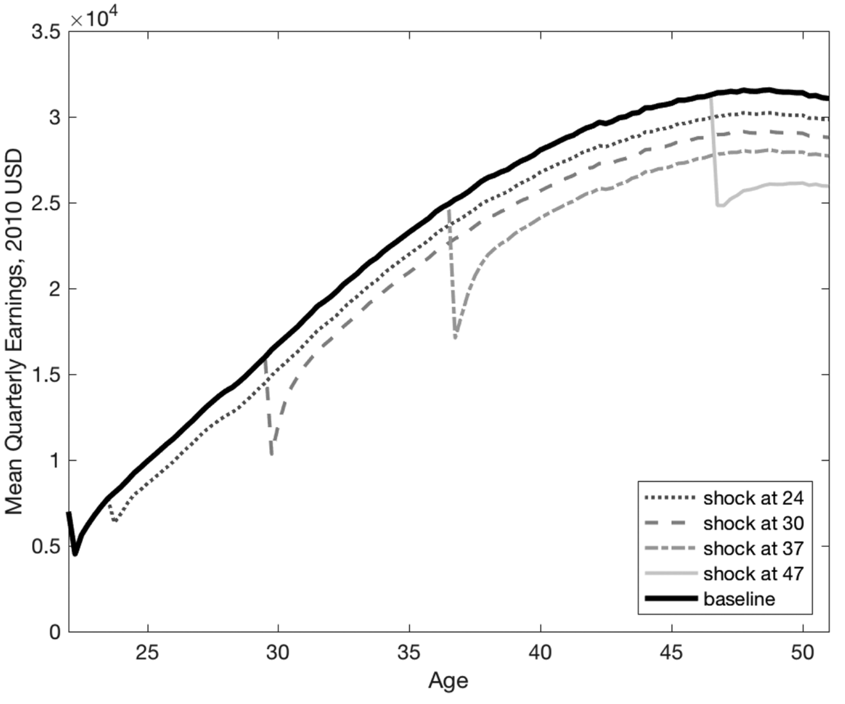

FIG. 8.—Effect of occupation-specific wage shock by age. This figure plots the average simulated earnings over the life cycle for workers who experience a 20% drop in wages in their current occupation at different ages. A color version of this figure is available online.

in other occupations. The exception to this pattern is workers who experience the shock at age 24. At this early point in their career, workers are searching through occupations to find a high-wage match. Because I do not incorporate on-the-job search, this churning means that many 24-year-old workers are already between jobs when the shock hits, so the effect on quit rates is smaller. Following this initial drop, wages rebound quickly as workers shift into new occupations. Only workers who experience the shock at age 47 continue to carry the bulk of their initial wage loss into retirement.

Table 5 quantifies these patterns. The first column reports the average decline in discounted lifetime earnings following the shock relative to the baseline simulations. Occupational mobility allows workers to substantially mitigate the effect of these shocks. Workers who are 24 when wages fall absorb on average well less than half of the shock: a 20% drop in current occupation wages generates only a 6% drop in average remaining lifetime earnings. The effect of this occupation-specific shock is monotonically increasing with age. Workers who are 47 at the time of the shock experience a

Table 5
Effect of a Permanent Occupation-Specific Wage Shock

Shock	Average Share of Remaining Earnings Lost (1)	Average Share of Lifetime Earnings Lost (2)	Share of Workers Who Quit following Shock (3)
At age 24	.060	.058	.724
At age 30	.095	.080	.696
At age 37	.134	.080	.537
At age 47	.177	.035	.289

NOTE.—This table presents the average effect of a simulated 20% fall in wages in workers' current occupation. Column 1 presents the average decrease in discounted lifetime earnings in all periods after the shock relative to the baseline simulations. Column 2 presents the average decrease in total discounted lifetime earnings relative to the baseline case. Column 3 presents the share of workers who quit their current occupation to look for other work within 2 years of the shock, including workers who were unemployed at the time of the shock or who were exogenously laid off within 2 years.

18% average decline in remaining earnings, almost the full impact of the initial shock.

Older workers absorb more of these occupation-specific shocks because they are less willing to change occupations following the shock. The last column of table 5 reports the share of workers who quit within 2 years of experiencing the wage shock.[24] Almost three-quarters of the youngest workers quit following the wage shock, while only 54% of midcareer workers and 29% of the oldest workers do so. This decline comes from two sources. First, older workers have substantially higher expected wages in their current occupation than in any other occupation. Wages rise rapidly in the first decade of work, first because workers search through occupations until they find a high-paying match and then because they begin to accumulate occupation-specific skills. A worker's occupation in his late thirties is the result of this search process, making it more costly to change occupations even after a fall in wages. Second, changing occupations requires a short-run cost (low earnings in unemployment) in exchange for the possibility of ultimately securing a job with higher wages. This trade-off is most likely to pay off for workers who have many years of working life left to enjoy the higher future wages. This effect explains the further drop-off in quit rates between ages 37 and 47.[25]

[24] I include workers who were unemployed at the time of the shock and workers who were exogenously laid off within 2 years of the shock in these shares. The second addition is never quantitatively important. The first is quantitatively important only for workers who experience the shock at age 24. Since most of the unemployed workers at age 24 found it optimal to quit to explore other occupations even before the wage shock, it seems most natural to include them as part of the share of mobile workers.

[25] The patterns in quit rates and earnings losses are similar if I divide workers by tenure rather than age, but they are somewhat less stark because the tenure division does not capture differences in accumulated search capital.

The decline in total discounted lifetime earnings relative to the baseline case (col. 2 of table 5) is hump shaped in age at the time of the shock. While the oldest workers experience the worst declines in earnings following the shock, their total discounted lifetime earnings are on average only 3.5% lower. These workers spend most of their working lives under normal conditions, so the large decline in earnings for the last 5 years of working life has a small effect on total lifetime earnings. The youngest workers have almost all of their working lives affected by the shock, but the shock is less costly for them. At age 24, workers are just beginning the search for a well-matched occupation. Many of these workers would have changed occupations in the next several years in any case, so a shock to their current occupation is not very costly. Workers who are in their thirties at the time of the shock experience the largest losses in total lifetime earnings. These workers are just old enough to have found a good match and accumulated some occupation tenure, making it costly to change occupations, but young enough to have most of their working lives affected by the shock.

Workers who remain in the affected occupation experience the largest percent declines in earnings. However, it does not follow that these workers are worse off than those who change occupations. Figure 9 plots average wage profiles for workers who experience an occupation-specific wage shock at age 37 separately for occupation movers and stayers. I classify workers as movers if they quit or are laid off within 2 years of the shock or if they were already out of work at the time of the shock. As shown in table 5, about half of workers fall into each of these categories. This division represents the desire to change occupations, but not all quitters end up doing so. Five years after the shock, 30% of quitters and 4% of stayers are in a new occupation.

Figure 9 illustrates why workers who remain in their current occupation even after a 20% drop in wages choose to do so. Prior to the shock, these stayers were earning substantially more than the workers who chose to quit. The gap reflects that stayers are more likely to be in high-paying occupations and also that they have higher average match quality. Average earnings for stayers never recover from the wage shock, but even after this substantial fall in earnings the average stayer earns slightly more than the average mover. Workers who choose to quit in response to the wage shock have lower earnings before and after the shock. However, these movers experience smaller long-run negative costs. Within 2 years they have almost the same average earnings as they receive in the baseline simulations.[26]

[26] A few of the workers who move after the shock do so because of an exogenous job loss or fall in wages that also occurs at this time in the baseline model. This phenomenon explains the slight dip at the time of the shock in baseline earnings for movers and the small hump for stayers, who are less likely to be receiving negative shocks at this point in the baseline simulations.

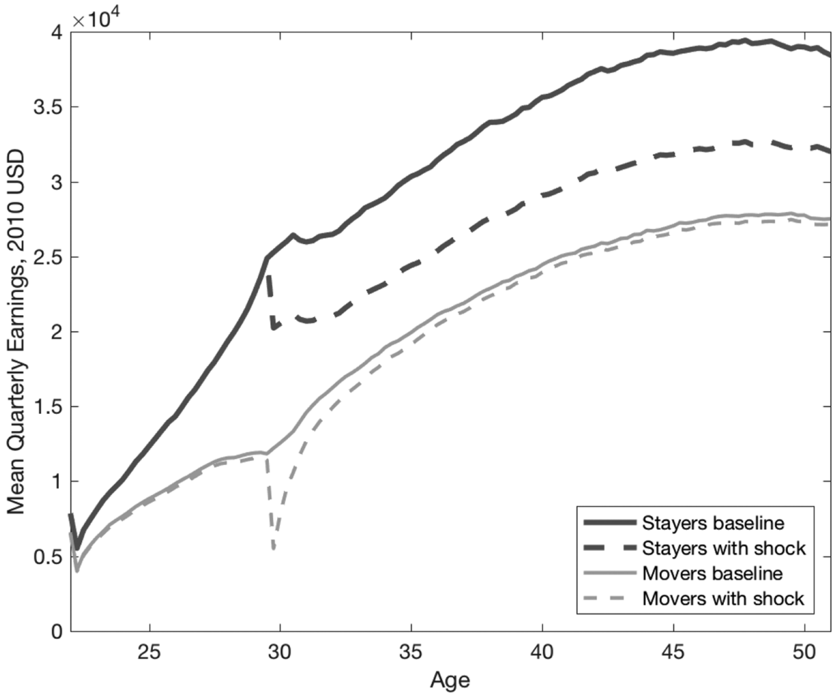

FIG. 9.—Effect of occupation-specific wage shock by mobility. This figure plots the average simulated earnings over the life cycle for workers who experience a 20% drop in wages in their current occupation at age 37. Workers are classified as movers if they quit or are laid off within 2 years of the shock or if they were already out of work at the time of the shock. A color version of this figure is available online.

Autor et al. (2014) consider a real-world analog to this wage shock simulation by looking at the employment choices and earnings of workers who began working in sectors of manufacturing with varying subsequent exposure to increased international competition. As predicted by this simulation, they find that workers exposed to more competition have lower future earnings and are less likely to remain in the same job than workers with less exposure. Unlike these simulations, they find that the highest costs of international competition are borne by workers with low tenure and relatively low wages in their starting occupation. This pattern may reflect differences in general ability across workers, which is present in the data but not my simulations. In reality, workers with relatively high wages in their starting sector are also likely to have higher wages in other sectors and are perhaps better able to organize a search for a new job. In my model, in contrast, workers with relatively high earnings in a given occupation were simply lucky in their match with that occupation. Those high wages say nothing about the worker's ability to successfully find other work. This occupation-specific match quality—and workers' accompanying reluctance to leave a good match—is surely also at play in the data, but it is dominated by fixed differences across workers.

VI. Conclusions

Workers who begin working in different occupations can expect to earn substantially different amounts over their working lives and will also be exposed to different levels of total earnings risk. This risk comes from shocks to wages and shocks to employment. Occupational mobility provides important insurance against wage and employment risk by allowing workers to escape some negative shocks. I describe and solve a model of optimal worker decisions over employment and occupation, including multiple sources of wage and employment risk and allowing workers to change occupations in response to these shocks. I estimate the parameters of this model and simulate streams of lifetime earnings. The variance of these simulated earnings streams measures the total earnings risk for workers starting in each occupation.

Risk varies widely across occupations. The variance of lifetime earnings is more than twice as high for workers who begin working in law as for workers who begin working in sales. Workers appear to recognize these differences in risk across occupations; the riskiest occupations pay more on average, consistent with a compensating differential for risk, and workers who are more risk averse tend to sort into the less risky occupations. The relationship between riskiness and expected earnings suggests that the average worker would give up at least 9% of total lifetime earnings in the riskiest occupation in order to reduce the riskiness of that occupation to the level of the safest starting occupation. Finally, occupational mobility provides a quantitatively important insurance mechanism against some earnings shocks. On average, workers who face a 20% drop in wages in their current occupation experience only a 12% drop in remaining lifetime earnings because many workers move jobs to escape the shock.

Compensation for lifetime earnings risk explains a large share of the differences in average lifetime earnings across occupations. However, the variation in lifetime earnings across individuals is far larger than the variation in these averages across occupations. Compensation for earnings risk is not an important driver of overall earnings inequality. Age, race, geography, and whether the worker completed college can explain about 20% of the variation in log weekly earnings for workers in the PSID with some college education. Adding my measure of occupation-specific earnings risk explains only an additional 2%.

Nonetheless, the strong relationship between lifetime earnings risk and expected earnings suggests that this earnings uncertainty is not insurable. If it were, workers would require only the price of this insurance to enter a riskier occupation. This uninsurable risk generates several inefficiencies in the labor market. Workers with different preferences for risk sort into occupations partially on the basis of the riskiness of earnings rather than matching only on their relative skills and enjoyment of the work. The extra compensation workers demand for enduring earnings uncertainty raises the price of the goods and services they provide without increasing the workers' utility. Public programs like unemployment insurance, food stamps, and progressive income taxes compress the earnings distribution and can reduce these inefficiencies while increasing workers' welfare. However, the classic principal-agent model suggests that workers must continue to bear some earnings uncertainty to maximize productivity.

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