Wage Risk, On-the-job Search and Partial Insurance

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Preliminary. Comments welcome.

Abstract

This paper contributes to the growing literature on modeling individual wage dynamics. I build and estimate an error component model of wage process jointly with a structural life-cycle model of job mobility in an economy with search friction and job-switching cost. Besides separating shocks by their persistence, I distinguish two sources of wage shocks: shocks at worker-firm level and shocks at individual level which apply to all firms and matches. Contributions of this approach are twofold. First, I show that worker's job-job transition serves as a valuable channel for employed workers to self-insure against match level wage shock. Second, the model is capable of recovering true wage risk that workers experience prior to self-insurance through job mobility. Observed wage changes are after job mobility decisions and hence are different than the true shocks that occur prior to job mobility. Preliminary estimation results suggest that match level wage shock is the dominating permanent wage risk facing workers. The insurance value of on-the-job search is substantial, and is more valuable for workers with smaller match component or smaller switching cost.

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1 Introduction

This paper contributes to the growing literature on modeling individual wage dynamics. I build and estimate an error component model of wage process jointly with a structural life-cycle model of job mobility in an economy with search friction and job-switching cost. Besides separating shocks by their persistence, I distinguish two sources of wage shocks: shocks at worker-firm level and shocks at individual level which apply to all firms and matches. Contributions of this approach are twofold. First, I show that worker's job-job transition serves as a valuable channel for employed workers to self-insure against match level wage shock[1]. Second, the model is capable of recovering true wage risk that workers experience prior to self-insurance through job mobility. Observed wage changes are after job mobility decisions and hence are different than the true shocks that occur prior to job mobility.

In a typical error component model of wage process, wage shocks consist of two parts differing in their degree of persistence: a permanent shock that is highly persistent over time and a transitory shock whose effect does not last long. The variance of these shocks measures idiosyncratic wage risk, which are usually identified from panels of observed wage outcomes. While this type of wage process has been the building block of life-cycle consumption and saving models with uninsurable idiosyncratic income risk[2] dating back to Friedman (1957), there are several limitations. Most importantly, the sources of wage shocks are overlooked. One central argument of this paper is that in a frictional labor market people could *select* certain part of their wages through job mobility. A first implication is that wage changes due to job mobility choices do not necessarily represent wage risk[3]. Further distinguishing wage shocks at match level[4] and at individual level, I demonstrate that people have the ability to self-insure against match specific wage shocks and thereby the true (ex-ante) wage risk are misspecified from observed (ex-post) wage outcomes. A bad permanent match specific wage shock is latent if a worker is able to sample another acceptable job offer in the same period. If a worker moves to a higher paid job after a short period, such permanent shock is identified as transitory from observed wage outcome although

[1]Job-job transitions have becoming a prominent phenomena in the US labor market. Nagypal (2008) finds that job-job transitions make up nearly 50% of all job separations during 1994 to 2007, twice as large as transitions from employment to unemployment. My own calculation confirms this empirical fact (see Section 4 for details).

[2]Among others see Deaton (1992); Carroll (1992); Gourinchas and Parker (2002). See Heathcote, Storesletten, and Violante (2009) for a review.

[3]Recent paper by Low, Meghir, and Pistaferri (2009) and Altonji, Smith, and Vidangos (2009) also make this point. I compare this paper to theirs in the next section.

[4]Henceforth I would only refer to it as match specific shocks (albeit it can be either purely firm specific or match specific), since empirically it is infeasible to distinguish pure firm effect from pure worker-firm match effect without employer-employee matched data.

the true shock was permanent. With shocks mixed with endogenous choice and self-insurance behavior, it is difficult to assess the true welfare cost of wage risk and evaluate the implications of government policy interventions.

This paper decomposes unexplained wage residuals for employed workers as a linear combination of individual component, match component, and transitory shocks. Each of the former two components follow a random walk process with random growth factor. The match component is firm-worker match specific, and can be interpreted as job-specific human capital or idiosyncratic firm effect on wages. In a labor market with search frictions, there is a distribution of firms offering the worker of a particular level of general skills different value of match[5]. This imperfect information structure in the form of search frictions carries two implications. First, employed workers are motivated to search on-the-job thanks to the dispersions of match component among jobs in the market and the stochastic match value of his current job. Second, workers are able to select their match component of wage as they locate better jobs over time.

To explain worker's job-job transition behavior, I build a dynamic discrete choice model of on-the-job search. The model features job switching cost and stochastic within-job wage changes as implied from the wage process. One implication of the model is that job mobility decision is only dependent on the match component of wages and other non-wage unobserved factors. This enables us to separate person-specific wages from match-specific wages if a panel of observed wage and job mobility information were given.

The model is estimated by Method of Simulated Moments using longitudinal data from the 1996 panel of Survey of Income and Program Participation. The key findings include the following: (1) Wage risk at match level could account for the majority of the wage risk facing workers. (2) The insurance value of on-the-job search is substantial and is particularly valuable for workers whose match component or switching cost is low. (3) Unobserved individual heterogeneity explains a major portion of the variance of wage at the beginning of work life. Over time, the contribution from match component of wages quickly rises and becomes a dominating contributor to the variance of wages for workers with

[5]This is rationalized by several search-theoretic models although with somewhat similar basic structure (See Eckstein and van den Berg (2007) for a comprehensive discussion). A number of papers have taken a game-theoretic approach: with heterogenous firms, in Burdett and Mortensen (1998), it is an outcome of noncooperative wage setting game among firms; in Mortensen and Pissarides (1994) it takes place through bilateral bargaining between workers and firms; in Postel-Vinay and Robin (2002) it results from wage renegotiation upon workers approached by more productive firms. Given the purpose of the paper and limitation of my data, I abstract from game-theoretic models of endogenous wage determination

over 10 years of labor market experience. (4) The estimated return to tenure is negative and the return to experience is positive. This is after accounting for endogenous job mobility decision in each period and heterogeneity in tenure and experience effect on wages. (5) Job switching cost is an important determinant of job mobility decisions.

The rest of the paper proceeds as follows. Section 2 describes this paper's relation to the existing literature. Section 3 introduces the wage process and builds a parsimonious on-the-job search model. It then illustrates the model's implications to wage risk and to partial insurance. Section 4 introduces the data set to be used and presents empirical evidence from data which motivates this study. Section 5 discusses estimation and identification strategy. Estimation results are presented and discussed in Section 6. Section 7 evaluates the insurance value of on-the-job search. Section 7 concludes.

2 Relation to Existing Literature

There is a substantial literature assessing the magnitude and persistence of idiosyncratic wage risk in the labor market. With few exceptions these papers specify exogenous error component model of wage process and fit it with observed feature of wage dynamics. These studies typically find a random walk process for the permanent component and a low order MA or ARMA process for the transitory component[6]. Some papers also emphasize the importance of initial heterogeneity in wage growth (random growth model) (e.g., Haider (2001); Guvenen (2007); Moffitt and Gottschalk (2008)). The wage process in this paper builds upon these findings.

Few papers so far attempt to identify the sources of transitory and permanent income shock. Gottschalk and Moffitt (1994) is the first study that I know which provides a suggestive empirical investigation of the causes of rising transitory variance of US male earnings in the 80s. Violante (2002) shows that skill-neutral technological change could result in a rise in the variance of transitory earnings, in a model where workers learn vintage-specific skills that are only partially transferrable across different machines (jobs). This paper relates to this scarce literature, with a focus on estimating the effect from one particular source: job mobility.

Two recent papers, Altonji, Smith, and Vidangos (2009) and Low, Meghir, and Pistaferri (2009),

[6]See, among others, Abowd and Card (1989); Moffitt and Gottschalk (1995); Meghir and Pistaferri (2004); Moffitt and Gottschalk (2008); Blundell, Pistaferri, and Preston (2008); Jensen and Shore (2008).

further advance the literature by modeling earning dynamics and job mobility jointly. Low, Meghir, and Pistaferri (2009) estimate a wage process taking account of individual's selection process between jobs and into and out of employment. Their estimates suggest that, once job mobility decisions are controlled for, the variance of permanent shock is much lower, suggesting that what has been identified as permanent wage risk from typical error component model contains variability due to responses to shocks through job mobility. Altonji, Smith, and Vidangos (2009) construct a rich statistical model of earning dynamics from equations governing wage determination, hours of labor supply, job-job transition and transitions into and out of unemployment. They show that job mobility and unemployment, among other factors, play a key role in the variance of earnings over career. Both papers, however, assume worker-firm match does not vary until the match is dissolved.

Continuing along this line of research, this paper proposes to further distinguish wage shocks that are match specific from person specific shocks. In modeling the wage process, one major advancement of this paper is that it describes a stochastic process for the match component analogous to the process on individual component. This introduces permanent and transitory wage risk that are particular to a job (worker-firm match), where on-the-job search emerges as a channel of self-insurance. In addition, Altonji, Smith, and Vidangos (2009) work with an econometric models without an utility maximization framework. While their descriptive statistical model may be attractive in many ways[7], specification of such model may suffer from arbitrariness without the guidance of a theory of individual choice. I formulate and estimate a structural on-the-job search model with wage uncertainty and job switching cost, which is similar to the approach taken in Low, Meghir, and Pistaferri (2009) but differs in estimation strategy. Their structural search model is used for welfare analysis after the wage process has been identified in a first stage. They estimate their wage process in the framework of incidental selection model separately from the search model. I adopt a more efficient estimation strategy by estimating the search model jointly with the wage process, since the search model implies structural selection process between jobs.

This paper also connects to other areas of research. It is related to a developing literature analyzing individual's channel of insurance beyond risk-free savings in an incomplete market[8]. Broadly, these

[7]Such as they include other events such as health shock and labor supply shock in the earning process besides job mobility.

[8]I should note that this literature primarily focus on channels of consumption insurance. This paper emphasizes job mobility as a channel for self-insuring income, since I do not model consumption choices in the on-the-job search model.

papers suggest that individuals self-insure wage risk through varying labor supply, family and public insurance programs[9]. I show that job mobility via on-the-job search can be another channel of self-insuring a particular type of wage risk.

This paper is also related to the partial equilibrium on-the-job search model in the literature[10]. An innovating feature in my model is that there are two unobserved wage component evolving stochastically. Match specific wage follows the stochastic process during a job tenure while the person specific wage process evolves during the life-cycle. Yet the decision rules can still be described by a set of reservation values. Moreover, this feature of the model may provide an alternative within the on-the-job search framework to quantitatively match the extent of job-job transitions observed in the US labor market, where the basic on-the-job search model has failed to achieve[11]. It also provides a parsimonious way to explain wage cuts in job-job transitions. Job mobility with wage cut has been difficult to reconcile in standard search model, because with stationary wage policy worker chooses to move only if a higher wage offer arises[12]. Lastly, to the best of my knowledge, very few papers in the job search literature consider the dynamic impact of job switching cost in determining worker's job mobility behavior except Hey and McKenna (1979) and Van Der Berg (1992). This paper demonstrates that switching cost is an important aspect of job search behavior.

[9]See Heathcote, Storesletten, and Violante (2009) for a review. Examples include Low (2005) (labor supply), Kaplan (2009) (within family), Blundell and Pistaferri (2003) (means-tested program), Gruber (1997) (unemployment insurance), Low and Pistaferri (2010) (disability insurance).

[10]Burdett (1978) is the pioneer work. See Mortensen (1986); Rogerson, Shimer, and Wright (2005) for a review.

[11]This problem is first recognized in Nagypal (2005). Several extensions of the model have been proposed. Nagypal (2005) incorporates a Brownian motion process that causes the value of a job to decrease at times, and Nagypal (2008) considers stochastic unemployment risk over a job tenure.

[12]Postel-Vinay and Robin (2002); Dey and Flinn (2005); Flinn and Mabli (2008) rationalize this behavior through an on-the-job search with wage renegotiation between worker and current employer responding to outside offers. Hedonic models may provide another explanation. Earlier structural estimation of search model (Wolpin, 1992) assume observed wages contain measurement errors.

3 The Model

3.1 The Wage Process

The life-cycle wage process for an individual i employed by firm j in his labor market age t is:

$$
\begin{aligned}
\ln \widetilde{w}_{ijt} &= \ln w_{ijt} + v_{it} \\
\ln w_{ijt} &= Z_i'\beta + a_{ijt} + u_{it} \\
a^l_{ijt+1} &= a_{ijt} + c_i + \eta_{ijt+1} \\
a_{ijt+1} &= \begin{cases} a^l_{ijt+1}, & \text{if no job change between } t \text{ and } t+1 \\ a^o_{ij't+1}, & \text{if job change between } t \text{ and } t+1 \end{cases} \\
u_{it+1} &= u_{it} + \delta_i + \zeta_{it+1}
\end{aligned}
$$

When a worker starts his work life, his initial wages are:

$$\ln w_{i0} = Z_i'\beta + a_{ij0} + u_{i0} \tag{1}$$

$$a_{ij0} \sim N(0, \sigma^2_{a_0}) \tag{2}$$

$$E(u_{i0}) = 0, var(u_{i0}) = \sigma^2_{u_0} \tag{3}$$

Assume that

$$E(\zeta_{it}) = 0, var(\zeta_{it}) = \sigma^2_\zeta \tag{4}$$

$$E(\delta_i) = \mu_\delta, var(\delta_i) = \sigma^2_\delta \tag{5}$$

$$E(v_{it}) = 0, var(v_{it}) = \sigma^2_v \tag{6}$$

$$\eta_{it} \sim N(0, \sigma^2_\eta), c_i \sim N(\mu_c, \sigma^2_c), a^o_{ij't} \sim N(0, \sigma^2_{a_0}) \tag{7}$$

with orthogonality between all five of these variables. $\ln \widetilde{w}_{ijt}$ is the observed real log hourly wage for worker i employed by firm j in labor age t. Z_i is a $K \times 1$ vector of exogenous regressors of observed heterogeneity including a constant[13]. β is a $K \times 1$ parameter vector. For an employed worker,

[13] The age profile of wages will be captured through estimated mean of random growth factors δ_i and c_i. See section 5 for details.

unexplained log wage residual is decomposed into three components: an individual component u_{it}, a match component a_{ijt} between firm j and worker i, transitory shock v_{it}. The former two components evolve independently under two parallel stochastic processes.

Individual component evolves over the life-cycle from an identically and independently distributed permanent random shock ζ_{it} and a random growth factor δ_i with mean μ_δ [14]. It corresponds to the concept of permanent wage in the literature, which is usually thought as representing return to skill or human capital. The random growth factor δ_i has cross-sectional variance σ^2_δ. The heterogenous but non-stochastic growth in individual component of wage may capture heterogenous return to work experience, perhaps through differential learning ability to general skills or human capital investment.

Parallel to the individual component, prior to selection between jobs, match component is a random walk process. Let a^l_{ijt+1} be the latent match at $t+1$ prior to job mobility. It evolves from random growth factor (drift) c_i with mean μ_c and cross-sectional variance σ^2_c and permanent shock η_{ijt}. Assume that η_{ijt} are identically and independently distributed across firm, worker and time[15]. Unlike person-level shocks, I impose distributional assumption on the match-level shocks and random growth factor. One interpretation of the match component is that it is an idiosyncratic firm effect which is a complement to the individual productivity. From the perspective of human capital theory, match component can also be regarded as job-specific human capital. Random growth factor c_i measures individual-specific growth of match value for an employed worker, which can be thought as return to job tenure or firm-specific human capital [16]. Shock to match component then represents a worker-firm specific permanent deviation from the mean growth rate. This would happen, for example, when in a particular year firm does not provide enough training to enhance worker's firm specific skills (negative η_{ijt}), or it adopts a new technology that is complementary to worker's productivity (positive η_{ijt}). In general it consists of both pure match-specific shock and pure firm-specific shock, although without firm level data, distinguishing between these is not feasible. More broadly, match component can be interpreted as any factor that affects worker's productivity with current firm but not after he leaves for other firms.

[14] In the literature typically $\mu_\delta = 0$. This is a normalization since Z already includes a constant and a term linear in age. I deviate from it because with job selection, wages are endogenous except the first period. See section 5 for details.

[15] Because of the independence assumption, for simplicity henceforth I drop the j subscript on η.

[16] This is more general than the prototype model of wage determination in the literature attempting to estimate return to tenure (Topel, 1991), in that here c_i is person-specific. An individual specific c_i would also facilitate in estimating the model (section 5). It would be interesting to model tenure effect as match-specific, so for the same worker, some jobs are expected to offer higher growth prospects but lower initial wage (compensating wage differentials). This would, however, introduce complexity to the search model because with an exogenous wage process I need to consider wage offers varying over both levels and growth rate. I leave it for future research.

Individual component measures worker's general productivity regardless of his employer[17]. Unlike the individual component, match component is firm-worker specific. Random growth factor and permanent shocks to the match component are accumulating only over the current job tenure and will "vanish" after a job change[18].

Topel and Ward (1992) and Flinn (1986) show the importance of match component in explaining wage growth among young workers. That log wages can be decomposed linearly in a worker component and a match component is rationalized by Postel-Vinay and Robin (2002) in a game-theoretic model. They demonstrate that in an equilibrium on-the-job search model with firm and worker heterogeneity and wage renegotiation, log wages can be linearly decomposed into a worker-specific component and a firm-specific component closely interacting with labor market frictions. Due to data limitations, I take a more agnostic approach. Worker's wage is determined in a simple partial equilibrium on-the-job search model. In an equilibrium model with wage bargaining such as the one considered in Postel-Vinay and Robin (2002), the match component can be thought as match rents accrued to the worker after worker-firm bargaining. In that context, match level shock may result from a shock to worker's bargaining power or a renegotiation on wages following a credible outside offer to the worker.

Job offer with match specific wages a^o ("o" stands for offer) is drawn independently from a stationary offer distribution. Assume it is a normal distribution with mean zero and variance $\sigma^2_{a_0}$ [19]. The independence assumption implies that offered matches are uncorrelated with worker's individual wage component, and hence each firm has constant return to labor technology and there is sorting in the labor market. For an individual choosing to start a new job in $t+1$, initial match component is an *accepted* random drawn from the offer distribution.

When worker i receives an offer from firm j' at time t, prior to making job mobility decision, worker is perfectly informed of his general productivity u_{it}, match-specific productivity a^l_{ijt} if he chooses to stay ("l" represents latent) and the value of the offer $a^o_{ij't}$[20]. At any time, workers have perfect information

[17] There is a distinction between job mobility between and within occupations, as estimates from Kambourov and Manovskii (2009) show return to occupational tenure is large, even after controlling for return to tenure and to experience. I ignore this issue for now. Accounting for mobility across occupation requires another model of selection process. A more interesting case is where variance of match level shock differ among occupations/sectors, so that people initially self-select into these occupations. I plan to add these features in future work.

[18] There is evidence that firm-specific human capital may be transferable between jobs at least partially (reference here). While the match process does not explicitly assume this feature, it is important to emphasize that the new accepted match would be positively correlated to the old match because of selection (a point I will emphasize later).

[19] The stationarity of the offer distribution can be relaxed. For example, Topel and Ward (1992) permits the offer distribution to mean-shift with individual's work experience.

[20] Another set of search models develop the idea that the value of a match is not known when firm and worker meet but

about their current match value, expectation of future match values and the distribution of match component in the labor market, but information of other job locations and their associated match value must be obtained through search. The stochastic processes of match values guarantee that the search process does not eventually lead to a competitive outcome where all workers end up with staying at the job of highest firm effect. I assume that none of the shocks to the u_{it} and a_{ijt} are anticipated by the worker so they represent wage uncertainty[21].

Transitory shocks are identically and independently distributed across individual and time. Transitory shock absorbs wage shock with no persistence, at either worker-firm match level or at person level. It also includes classical measurement errors on reported wages. To simplify the problem, I assume that transitory shocks affect wages *after* mobility decision is made in each period, and therefore given it is serially uncorrelated it is unrelated to job mobility choices[22].

My wage process bears similarities to Low, Meghir, and Pistaferri (2009) and Altonji, Smith, and Vidangos (2009). One major contrast is that in those papers match component is constant during a job tenure[23] and therefore there is no match specific wage risk except unemployment risk in the form of job destruction. Having a process for both match component and individual component is crucial for on-the-job search to serve as a channel for partial insurance (see Section 3 for details) and therefore identify the true wage risk facing individuals.

3.2 The On-the-job Search Model

I now present a simple dynamic discrete time model where individuals conduct on-the-job search given the wage process described previously. Workers begin employment in $t = 0$ by receiving a random job offer. Each job offer is characterized by a match valued between the worker and the firm. At the beginning of each subsequent period they make the following discrete choice: move to a different job if an offer arrives, or stay with the current job possibly paying a different wage. On-the-job search is

is updated ex-post as more information arrives. See Jovanovic (1979).

[21]See Cunha and Heckman (2007) for an illustration of how this might be a problem.

[22]Many papers, e.g. Moffitt and Gottschalk (1995, 2008); Haider (2001); Meghir and Pistaferri (2004), show that there are some serial correlation over time in the transitory shocks. All these models do not model match component in wage process and thus do not analyze the effects of job mobility on wages. Job mobility is regarded as the main contribution to transitory shocks (Gottschalk and Moffitt, 1994).

[23]Low, Meghir, and Pistaferri (2009) experiment a random walk process of match component with individual fixed effect u_i as an alternative specification (section 6 of their paper), and conclude that it doesn't fit the data very well. However, they conjecture that some ''combined aspects of stochastic specifications" may do better. In this sense, this paper advances their research agenda.

costless. However, when workers switch jobs, they have to pay a one-time switching cost. Switching cost captures unobserved non-wage factors that drive job mobility choice, which may include, for example, relocation cost and any fringe benefits a worker has to give up if moving to a different job.

I focus on worker's job-job transitions and ignore worker's voluntary and involuntary transition to unemployment. Ignoring worker's involuntary transitions means there is no layoff risk. It's easy to show that having an exogenous probability of worker-firm dissolution does not change worker's job change rule, although match specific wage risk will be larger if there is a probability of match dissolution. Neglecting voluntary unemployment eliminates unemployment from worker's choice set. This assumption is made for three reasons. One is that the focus of this paper is the interaction between job-job transitions and wage dynamics. Second, from an empirical point of view, job-job transition is the dominating phenomenon for workers in the US labor market compared with transition from employment to unemployment. For working-age male workers, my calculation shows that job-job transitions happen more than twice as often as transition from employment to unemployment (voluntary and involuntary combined)[24]. Third, for young male workers which structural estimation of the model is based upon, their value of nonmarket time (e.g. value of leisure and home production) is arguably small. On-the-job search combining with stochastic wage changes implies that the option value of unemployment search is very small. These factors lead to a small reservation wage for employment, making quit to unemployment an unlikely choice.

Individuals maximize the expected value of the discounted sum of a time-separable utility function

$$\max_{M_s, s=t,t+1,\ldots,T} \; E_t\left[\sum_{s=t}^{T}\Gamma^{s-t}(u(C_{ijs}) - M_{is}k_{is})\right]$$

subject to

$$C_{ijs} = w_{ijs}, \; \forall s = 0 \ldots T$$

when employed by firm j in period s. Γ is the discount factor and E_t the expectations operator conditional on information available in period t. k_{is} denotes utility loss in period s if worker switches jobs ($M_{is} = 1$). Assume $k_{is} = k_i + \kappa_{is}$, where $\kappa_{is} \sim N(0, 1)$, and k_i is expected to be positive. κ_{is} is a

[24]This number is in line with estimates reported in Nagypal (2008)

serially uncorrelated shock to switching cost. C_{is} is the consumption of individual i in period s, which is equal to his wage rate in that period. Consistent with the majority of search models, I do not model worker's saving choices although it is interesting to expand the model along this direction in future work. Individual's utility function is assumed to be the form of $u(C) = \frac{C^{1-\rho}}{1-\rho}$, where ρ is the degree of risk aversion. For convenience I assume that $\rho = 1$ which implies that $u(C) = ln(C)$. As it becomes evident later, the functional form of the utility function is inconsequential to individual's job-job choice rules. Hours of labor supply is assumed exogenous and inelastic. Wage evolves according to the wage process specified before.

Figure 1 depicts the process of job mobility decisions. At the beginning of each period, worker receives an offer from a different firm with probability λ^e [25]. If he accepts the offer, his match component for this period will be the match value offered by the new firm. His (residual) wage in this period will be the sum of the offered match value, this period's individual component plus any unexpected transitory shock. If he rejects the offer, his wage paid by the current employer then adjusts to a new level to absorb the contemporaneous tenure effect, shocks to individual and match component of wages, and transitory shock. In the discrete time model, worker has to sit out at least one period if he chooses to stay with his adjusted match value, before sampling a wage offer from another firm.

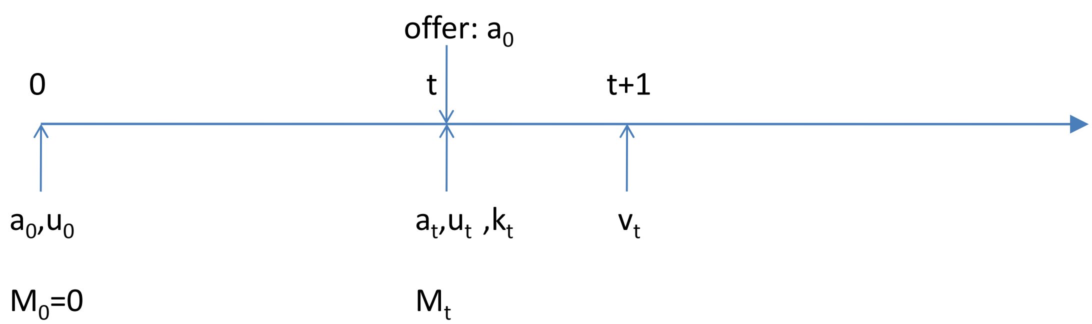

Figure 1: Process of job mobility decisions

Letting $S(t)$ represent the set of all state variables at time t, the value function for a worker i

[25] Following the literature of estimating partial-partial equilibrium search models, offer arrival probabilities are exogenous and therefore I do not consider the matching function formulation.

employed by firm j in period t is defined by[26]:

$$V_t^e(S(j,t)) = \begin{cases} V_t^e(S(j,t), M_t = 0), & \text{if no offer arrives in period t} \\ \max\{V_t^e(S(j,t), M_t = 0), V_t^e(S(j',t), M_t = 1)\}, & \text{if there is another offer from firm } j' \text{ in period t} \end{cases}$$

where

$$\begin{aligned} V_t^e(S(j,t), M_t = 0) =& \ln w_{jt} + \Gamma(1-\lambda^e)E_t\left[V_{t+1}^e(S(j,t+1))|S(j,t))\right] \\ &+ \Gamma\lambda^e E_t\left[\max\begin{Bmatrix} V_{t+1}^e(S(j,t+1), M_{t+1} = 0|S(j,t)), \\ V_{t+1}^e(S(j',t+1), M_{t+1} = 1|S(j,t)) \end{Bmatrix}\right] \\ V_t^e(S(j,t), M_t = 1) =& V_t^e(S(j,t), M_t = 0) - k_t \end{aligned}$$

The set of state variables includes all variables that provide information on worker's current and future wages and mobility decisions. State variables are indexed by j in order to highlight the stochastic evolvement of match specific wage component. Note that $V_t^e(S(j,t), M_t)$ represents the choice specific value function because felicity function depends on M_t. Similar to most optimal stopping problems, optimal solution is characterized by a threshold reservation value where a worker chooses to move if the offered match is larger than the threshold. In the next two subsections I discuss the solution under two specifications of the model.

3.2.1 Case 1: no switching cost

If $k_t = 0$, then $V_t^e(S(j,t), M_t = 0) = V_t^e(S(j,t), M_t = 1)$ for current period utility can be written as $\ln w_{jt} = Z'\beta + a_{jt} + u_t$ regardless of mobility choice in t. Since person component and match component evolves independently and are linearly additive, I decompose $V_t^e(S(j,t))$ into the sum of $V_t^e(S(j,t)^a)$ and $U(t)$ where $U(t)$ measures the expected life-time value of individual wage component and contributions from observable characteristics. $U(t)$ is not firm-specific and is independent of mobility choices[27]. The

[26] I omit the person subscript i from here on.

[27] The intuition is that worker's mobility decision is based on $\Delta V = V_t^e(S(j,t), M_t = 0) - V_t^e(S(j',t), M_t = 1)$. $U(t)$ is canceled out in ΔV and hence state variables other than $S(j,t)^a$ do not affect worker's behavior.

worker's problem can be re-normalized into

$$V_t^e(S(j,t)^a) = a_{ijt} + \Gamma(1-\lambda^e)E_t\left[V_{t+1}^e(S(j,t+1)^a)|S(j,t)^a)\right]$$
$$+\Gamma\lambda^e E_t\left[\max\begin{Bmatrix} V_{t+1}^e(S(j,t+1)^a, M_{t+1}=0|S(j,t)^a), \\ V_{t+1}^e(S(j',t+1)^a, M_{t+1}=1|S(j,t)^a)\end{Bmatrix}\right]$$

where the subset of state variables $S(j,t)^a$ includes $\{a_{jt}, c\}$. This normalization reduces the number of state variables. Proposition 1 below establishes that under zero switching cost worker is myopic when making job-job transition decisions.

Proposition 1. *If there is no job switching cost, then workers switch jobs if and only if there exists an offer whose match value is larger than their current value of the match.*

Proof. See Appendix A. □

Proposition 1 means that the reservation value for job change is just the contemporaneous match. It is well known that in the canonical on-the-job search model workers choose to switch jobs if offered wage is higher than current wage (Burdett, 1978). Wage uncertainty,however, does not have any impact on workers job mobility decision. This result is not surprising given our assumption of the wage process. A job offer from another firm and worker's match with current firm differ only in their initial levels: worker-firm level wage risk is the same across all firms, and deterministic wage growth is person specific and not firm specific. Thus without switching cost, the continuation value between staying with the current firm and moving to the other firm is the same conditional on a_{jt}. Worker's decision is only based on a comparison between the contemporaneous utilities from two firms.

3.2.2 Case 2: with job switching cost

In light of nonzero switching cost, the reservation match is implicitly defined by:

$$V_t^e(S(j,t), M_t = 0) = V_t^e(S(j',t), M_t = 1)$$

The expected value of a job offer must exceed the current value of the job plus the cost of switch. Re-normalizing the agent's problem as we did for the first case, the set of state variables again can be reduced to $S(j,t)^a = \{a_{jt}, c, k_t\}$.

Proposition 2 below establishes that the optimal strategy of job mobility is to move if the value of an offer is larger than worker's reservation match value. Let $h_t(a_{jt}, k_t)$ define the reservation match in period t conditional on worker's type c, and $a^o_{j'}$ be the value of an offer from a different firm.

Proposition 2. *If $k_i \neq 0$, a worker's optimal strategy is to set a reservation match value $h_t(a_{jt}, k_t)$ where a worker chooses to move if and only if $a^o_{j'} > h_t(a_{jt}, k_t)$. Furthermore, for all $t = 1 \dots T-1$, reservation match satisfies the following properties: (1) $h_t(a_{jt}, k_t) > a_{jt}$ if $k_t > 0$ (2) $0 < \frac{\partial h_t(a_{jt}, k_t)}{\partial a_{jt}} < 1$ (the second inequality implies that $h_t(a_{jt}, k_t) - a_{jt}$ is a decreasing function of a_{jt}) (3) $\frac{\partial h_t(a_{jt}, k_t)}{\partial k_t} > 0$.*

Proof. See Appendix A. $\square$

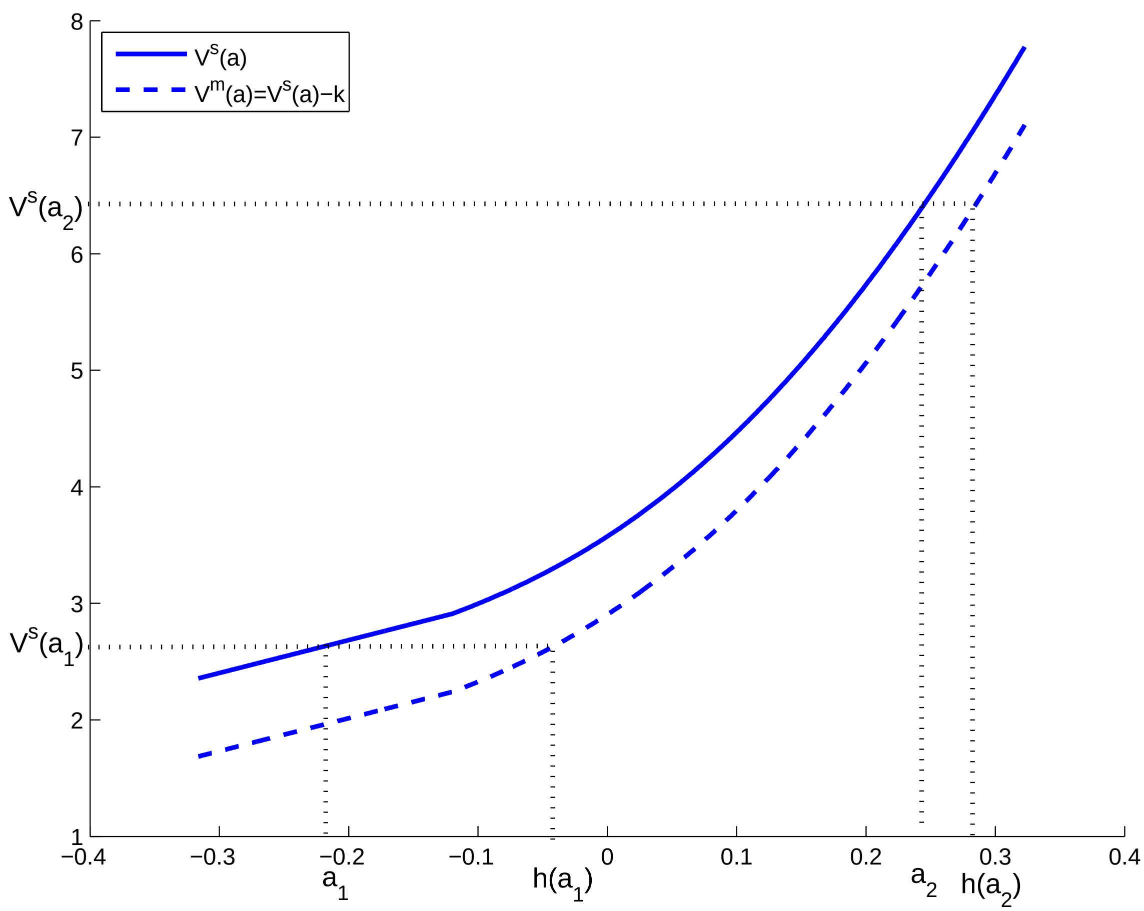

Figure 2: Value function and reservation match

Figure 2 shows the choice-specific value function for a given worker at $t = 3$. The solid line represents $V_t^e(a_{jt}, M_t = 0)$, and the dotted line is $V_t^e(a_{j't}, M_t = 1)$ given a specified value of switching cost $k_t > 0$. The function is increasing convex in a, a result that is proved formally in Appendix A. Given switching cost k_t, the reservation match is defined at $h(a)$ at which the worker is indifferent between moving and staying.

The first property of the reservation match is a direct implication from the monotonicity of the value function. If switching cost is positive, worker will always set the reservation match higher than the match paid by the present firm. This is another source of labor market inefficiency besides search friction. In a dynamic model where agents are forward-looking, the reservation match needs to include the expected discounted long-run compensation of the switching cost that has to be paid upon moving.

The second property characterizes the dynamic impact of switching cost on job mobility behavior. As illustrated on the graph, conditional on k_t, the convexity of the value function implies that the gap between the $h_t(a_{jt})$ and a_{jt} is smaller as a_{jt} grows. The economic intuition is that worker whose match is low expect more job changes in the future. For these workers, conditional on k_t and c_i, their optimal strategy is to set a larger gap between the reservation match and their match a paid by the current firm. These workers are more likely to receive an acceptable offer in the future, and by setting the gap "large", they avoid paying too much switch cost before reaching a high wage level. These results are similar to earlier papers analyzing the dynamic effect of switching cost in canonical on-the-job search models (Hey and McKenna, 1979; Van Der Berg, 1992).

In both cases, workers who have a high match component of wages are less likely to sample better offers to induce a job change, generating negative correlation between wage and job duration hazard.

3.3 On-the-job Search and Partial Self-insurance

In this section I highlight the role of on-the-job search as a channel of self-insurance. For illustrative purpose, suppose the individual component is fixed at zero and there is no transitory wage shock, return to tenure and switching cost. A worker initially gets paid by her match component a_0. Figure 3 describes an employed worker's dynamics of match specific wage under the model. At the beginning of period t, she suffers a permanent negative match specific shock η, and her new wage $a_1 = a_0 - \eta$ is such that $a_1 < a_0$. It is important to recognize that the permanent wage drop considered here stems from a pure idiosyncratic firm effect and does not mean a depreciation of general individual productivity. In the absence of on-the-job search, her wage is expected to remain at a_1 as long as she stays employed because the shock is permanent in nature.

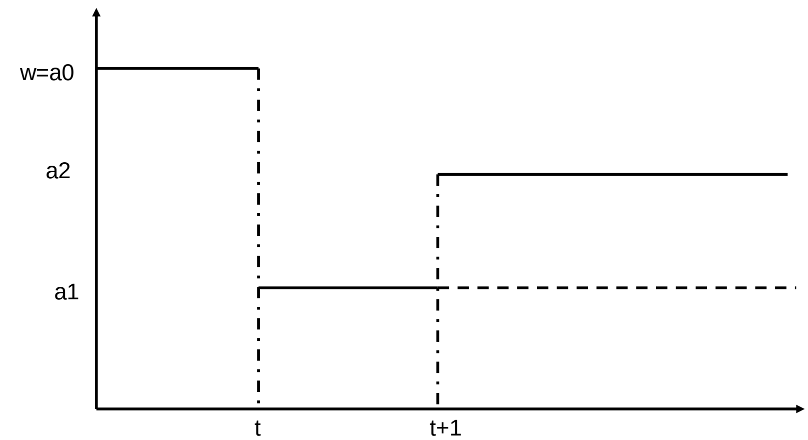

Figure 3: Match component and job change

With on-the-job search, she is able to self-insure against part of the match shock to wages. I consider two scenarios. First, suppose fortunately she receives an offer $a_2 = a_1 + \theta\eta$ at $t + 1$ with $\theta > 0$. θ is a measure of insurance in this context: $\theta = 0$ if there is no insurance, and $\theta \geq 1$ means the worker could fully self-insure against wage shock[28]. Then she would change job and earn wage a_2 for it gives her a higher expected wealth. By doing so, she manages to turn the initial permanent wage shock into effectively partly transitory and partly permanent. How quickly she finds an acceptable offer depends on offer arrival rate[29] and distribution of match offers, which introduces new uncertainties (these are termed employment risk in Low, Meghir, and Pistaferri (2009)). This at least suggests two shortcomings of standard approach of decomposing wage risk:

1. Wage increase from a_1 to a_2 results from an endogenous job mobility, not wage risk[30];
2. Initial drop η is perceived as a large permanent shock, but part of it ($= \theta\eta$) is identified as

[28] θ could be larger than one because a_2 is a random draw from the (truncated) offer distribution.
[29] The mean waiting time of a job offer for an employed worker is $1/\lambda^e$.
[30] Low, Meghir, and Pistaferri (2009) argues the same point.

transitory. Only for some worker who remains at a_1 for a long time, the initial shock is correctly identified.

Figure 4 depicts a second match dynamics in a similar setting. The only difference is that worker is able to locate a better job within period t. The observed wage rate in period t is a_2, underestimating the magnitude of original shock. Observed average wage per period alone mitigate initial wage risk facing workers, as it is combined with worker's self-insurance response to latent shocks. With wage process and mobility choice, the model is able to recover moments of the true wage cut.

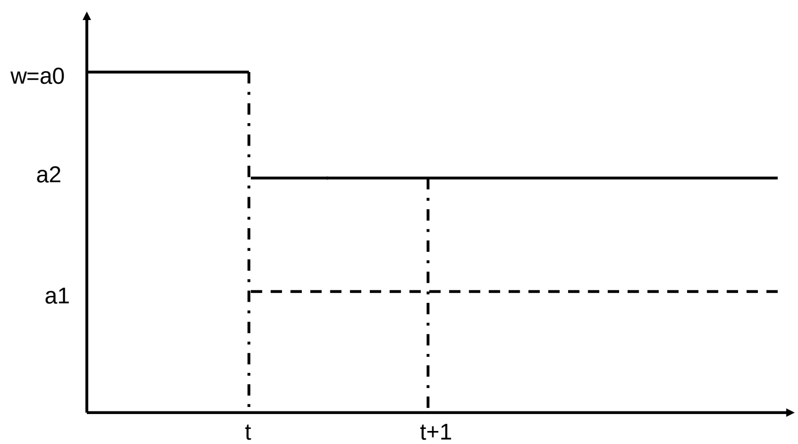

Figure 4: Match component and job change

Key driving forces in this setup are search friction and on-the-job search. The former justifies idiosyncratic firm effect and permanent match-level shock; the latter implies that workers are able to undo part of the match shock through job change. On-the-job search explains job-job transition, which in turn may help worker to partially smooth out negative match shock to wages. If there is heterogeneity in individual's offer arrival rate and/or match offer distribution, then individuals whose offer arrives faster and whose match offer is more favorable appear better self-insured. Moreover, even though individuals are assumed to have the same offer arrival rate and distribution of job offers, one implication from the model is that this insurance channel is more valuable for workers who have less match with the firm. The implied probability of job-job transition is $\lambda^e\left[1-\Phi(a)\right]$, so workers with high value of match are less likely to sample a better job and thus are less self-insured through job change than workers with low match specific wage, given the same magnitude of permanent match level shock. This implies that match specific permanent shocks appear more persistent on high match workers and more transitory on low match workers. If one expects that more educated workers acquire job-specific skills faster and build up a higher match on average, then this implication from the model coincides with the empirical evidence where studies find the proportion of variance of permanent shocks in total variance of income shocks are much higher for the more-educated than the less-educated. For example, taking estimates from Table I and III of Meghir and Pistaferri (2004), a simple calculation shows that for college graduates, the variance of permanent shock account for 67 percent of variance of (unexplained) earning growth, but the number drops to 27 percent for high school graduates and 20 percent for high school dropouts.

Variance of permanent match level shock, σ_η^2, measures wage risk prior to self-insurance. Recall that η is the permanent shock which people could select upon by moving to a job with higher paid match value. The properties of initial match value shows how the selection mechanism work in the model. For example, a negative match shock increases the probability of accepting an offer but decreases the expected value of the offer on current and future spell of the job. Due to job mobility, a worker is able to locate job j' such that $a_{ij't} - a_{ijt-1} > a_{ijt} - a_{ijt-1} = \eta_{it} + c_i$, i.e. people indeed are able to "undo" some part of negative match shock. Therefore using observed wage change to estimate $var(\Delta a)$ provides a misleading picture on the true wage risk facing workers. σ_η^2 should be the primary interest to policy makers. In the next few section, I describe how σ_η^2 is identified from the structural model, and provide measures to quantify the importance of this insurance mechanism.

Permanent individual shock itself cannot be insured through job-job transition for jobs only differ in the value of match. This again demonstrates the usefulness of distinguishing between permanent shock to match component and to individual component: although both represent wage risk, they differ in their channel of insurance.

Lastly, note again that having a process for match specific productivity a_j seems important. If match effect a_j is constant as in Low, Meghir, and Pistaferri (2009), then there exists no match specific wage shock. Job mobility never can be a channel for partial insurance against wage shock since the only form of wage shock is person specific. There is also no latent wage shocks per se in that context.

4 Empirical Evidence

4.1 Data and summary statistics

The data set I exploit is the 1996 panel of Survey of Income and Program Participation (SIPP). The 1996 SIPP is a four year panel comprising 12 interviews (waves). Each wave collects comprehensive information on demographics, labor market activities, types and amounts of income and participation in welfare programs for each member of the household over the four-month reference period. SIPP assigns unique job ID and asks job specific monthly earning for primary and secondary job that respondent holds. This feature, together with a relatively short recall period, makes it an attractive data set to study short-term job mobility and wage dynamics[31].

I focus on primary job, which is defined as the job generating the most earnings in a wave. Although SIPP has monthly information on job change and earnings, the time unit in the analysis of this paper is four month (a wave). This avoids the seam bias if we were using monthly variables. Real monthly earning and wage is derived by deflating the reported monthly earning and wage by monthly US urban CPI. Reported hourly wage rate is used whenever worker is paid by hour. For these workers, real wage per wave is the mean of monthly real wage over the four-month. For workers who are not hourly paid, their real wages are obtained by dividing real earnings per wave by reported hours of labor supply per wave[32]. Job change is identified from a change in job ID between waves. If an individual is unemployed through the wave, no job ID would be assigned.

The original SIPP 1996 panel has 3897177 person-month observations. I drop female, full time students, the self-employed, the disabled, and those who are recalled by previous employer after a separation. I trim the population whose real wage falls into the top and bottom 1% of the real wage distribution by wave. Because there is no unemployment state in the model, unemployed workers and people have intervening periods of unemployment are dropped.

When a worker is interviewed in the first wave of SIPP, it's likely that he has already worked for a job for certain periods. The situation is moderately better because in the first wave of SIPP, respondents are asked of the starting date of the present job. I use this information to construct correct job tenure

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

[32] For each month, respondent reports hours of work per week and how many weeks worked. Monthly labor supply is calculated as hours per week$\times$(weeks worked/weeks in month)$\times$4.33

for workers with elapsed job duration when they are first sampled. Subsequently, the tenure of the present job in next wave is just the recoded job tenure plus one unless a job change is observed in the sample. In this way, worker's job tenure and wage information is available through the sample period.

As explained section 5, I solve the initial condition problem by simulating the model from the first period in work life. This requires one to observe the complete employment histories for any given worker. As an approximation, I consider job starting between 20-26 as worker's first job in the life cycle[33]. This leads me to select workers whose calendar age is between 20-26 at the time when their present job started, in addition to the sample restriction described previously. I further restrict the sample to include young workers aged at or below 30 when they first enter the sample. So when a worker is sampled, the maximum possible elapsed job duration is $(30-19)\times 3 = 33$ periods. I then keep workers who are included in SIPP for at least eight waves, and construct a balanced 8-period panel of 1211 workers.

Summary statistics are provided in Table 1. Table 2 reports the distribution of total number of observed job changes in the sample. Initial experience level refers to the labor market experience observed in the first observation period. Since the selected sample consists of young workers, nearly 50% of the workers switch jobs at least once in the four-year sample period. The extent of job-job transitions decrease monotonically with workers' labor market experience. To investigate the influence of observed heterogeneity on the pattern of job-job transitions conditional on experience, I estimate a Tobit model of total number of job changes using all workers. Table 3 shows the results. Conditional on experience, there is strong evidence that workers who are paid by hour have more job-job transitions. It also appears that workers who are not married, white and less educated experience more job mobilities although such evidence is not statistically significant.

4.2 Wage Growth and Job Mobility

So far I have conceptualized job-job transition as a channel for insuring job specific wage risk. The key elements of the model is that match quality is a stochastic process upon which worker's job-job decision relies. This section derives empirical implications on worker's wage and mobility patterns from data. In specific, I ask two sets of questions: First, what is the pattern of within job wage

[33] It's notoriously difficult to determine the time when a sampled individual enters the labor market and starts employment. I believe this assumption is a reasonable approximation.

growth and in particular how common is real wage cut? Second, what is the empirical relation between within job wage growth and worker's subsequent mobility choice? Are workers who experience within job wage cuts more likely to change jobs? Recognizing that job specific match is unobserved and job mobility decision is endogenous, the empirical evidence provided here does not carry any structural interpretation. Nevertheless, empirical evidence serves as useful benchmark to evaluate the assumptions and implications of the model.

Figure 5A depicts unconditional distribution of within and between job real wage growth[34]. Wage growth is calculated as changes in log real wages in every four months. Two features of the picture are eminent. Firstly, between job wage growth has larger variation than within job wage growth, a feature consistent with the model because new job offers are random draws from a given distribution. Secondly, both within job and between job real wage cut is very common. Around 45% of job-job transitions end up with wage cuts, and a little less than 50% of within job wage growths are negative. The majority of the wage cuts are small in magnitude. The median within job real wage cut is at merely 1.3% per period. There remains, however, substantial portion of within job wage growth showing significant drop. 15% of the workers report within job real wage decline of 11% or more between waves. Wage cut between jobs is much greater: the median between job wage decline is about 20%. Measurement error may be an important contributor, as I discuss momentarily. Part of this could also be due to the stickiness of wages which are not keeping up with rising cost of living index in the short run. Figure 5B shows the distribution of between and within nominal wage growth. While the majority of the workers experience nominal wage growth, the amount of workers that had a nominal wage cut remains substantial.

The first two columns of Table 4 report descriptive regressions of log wage and mobility on lagged log wages and lagged job mobilities. Current and two period lagged mobility is not significant in 1a, and two period lagged log wage is insignificant in 2a which could be due to measurement errors in observed wages (see below). The rest of the coefficients are significant and generally show up with the expected sign. These two regressions will be run on simulated data using the estimates from the on-the-job search model (see section 6).

Next I investigate the empirical relation between within job wage growth and worker's subsequent mobility choice. In specific, suppose we have a worker employed by firm j at time $t-2$ and $t-1$.

[34]Throughout this section, wage refers to real wage unless otherwise noted.

Within job wage growth at $t-1$ is calculated by differencing $ln(w_{t-2})$ and $ln(w_{t-1})$. Since we observe his job history with firm j, we know his job tenure at $t-1$ and $t-2$. The question of interest is that whether a worker whose within job wage growth is low in period $t-1$ is more likely to move to another job in t. I estimate a probit model of job mobility on lagged wage growth. Table 5 reports the result. Column (1) shows the probit regression on one-period lagged within job wage growth without any covariates. In (2) I add in lagged job tenure and in (3) I further control for two period lagged level of wage and lagged experience. The on-the-job search model implies that job tenure is negatively correlated with probability of future job change, and workers whose level of match are high are less likely to sample an acceptable offer and switch jobs. As expected, the estimated parameters on tenure and wage level are significantly negative. The experience parameter is insignificant, which coincides with model's assumption that general human capital accumulation is independent of job mobility. Column (4) and (5) also controls for two period lagged within job wage growth. In every specification, the coefficient on within job wage growth is negative and statistically significant. This means that workers who experience smaller within job wage growth are more likely to change jobs in the coming periods, even conditional on job tenure, labor market experience and initial level of wage.

4.3 Measurement Error

In household surveys like SIPP, observed wages may be different from true wages because of reporting error. In our sample, measurement error in wages may come from three sources: from reported wages for those who are hourly paid, and from reported earnings and/or reported hours. Assuming that these reporting errors are classical (i.i.d), the extent of wage cut documented previously may be an overstatement of the true wage changes. Gottschalk (2005) uses earlier waves of SIPP and estimates that as much as three quarters of observed decline in within-job nominal wages reflect measurement error. Our wage process incorporates classical measurement error in the transitory component of wages v_{it}. As we will see later, the estimated variance of transitory wage shock is fairly large, suggesting that measurement error indeed may potentially have a large impact on cross-sectional variations of observed wages.

Classical measurement error adds noise to true wages which would obscure the relation between job mobility and wage. If within job wage changes are completely measurement errors, there should be zero correlation between worker's job mobility choices and wage movement on the job. However, probit regressions in Table 5 demonstrate strong correlation between observed within job wage change and job mobility choices. With classical measurement error, the coefficient estimates on within job wage growth term in Table 5 is biased downward, indicating that the true empirical relation between wage growth and job mobility is even stronger.

For nonclassical measurement errors, studies typically find little effect of nonclassical measurement error on earning mobility and covariance structure of earnings[35]. The more difficult question is whether measurement error is correlated with job mobility behavior. This could happen, for example, if the reporting error is smaller for workers with longer accumulated job tenure. Further empirical studies in this area is needed for future research.

I view the empirical results documented above as strong evidence for job mobility as a responsive behavior to wage risk. It is useful to reiterate that these empirical relations does not carry any casuality interpretation. Within job wage growth comprises both transitory and permanent wage shock at both worker and match level. Permanent match shock affects worker's present and future mobility choice. All of these are difficult to incorporate in a simple nonlinear regression framework. I now turn to structural estimation of the search model, where the selection mechanism is explicitly modeled.

5 Identification and Estimation Strategy

The estimation consists of two steps. In a first step, I estimate the earning regression and produce a consistent estimator of β. Recognizing the analytical complexity of evaluating conditional expectations in theoretical moments, the second step uses Method of Simulated Moments (MSM). The MSM numerically simulates the expectation of wage and job mobility, and then minimizes the distance between the simulated moments and empirical moments derived from data[36].

[35] See Gottschalk and Moffitt (2009) and the reference therein.

[36] The primary reason for choosing MSM over a maximum likelihood estimator is that to construct the likelihood function, one needs to integrate out the person component of wage u in every period. As the illustration below goes, the first- and second-moments of person-specific wages carry a tractable analytical form that is easy to evaluate.

5.1 The empirical model

As documented in the empirical evidence section, single workers and in particular workers who get paid by hour tend to make more job-job transitions. Motivated by this fact, I begin by allowing the mean of switching cost to vary with observable X:

$$k_{it} = \mathbf{X_i}'\mathbf{\Upsilon} + \kappa_{\mathbf{it}} \tag{8}$$

Vector X includes a constant, marital status, whether paid by hour, two education dummies(high school, at least some college) and race. As defined previously, κ_{it} is the i.i.d random shock to switching cost with mean zero and variance normalized to one. $\Upsilon = \{\gamma^{constant}, \gamma^{married}, \gamma^{hourly}, \gamma^{hs}, \gamma^{college}, \gamma^{race}\}$ is the vector of coefficients. One would expect that it's more difficult for married workers to change jobs because coordination problem within household adds more friction in the labor market. Hourly paid workers may find it less costly to move on average possibly because of the smaller fringe benefits they have to give up compared with workers who are paid by a salary. Each of X_i in X is measured in the first observation period and is assumed time-invariant starting from the beginning of life. Thus I do not exploit within person variations in job switching cost. [37]

Next, let us lay out the empirical model for two specifications of the search model. Recall that the wage equation for an individual i employed by firm j in his labor market age t is:

$$\ln \widetilde{w}_{ijt} = \ln w_{ijt} + v_{it}$$

$$\ln w_{ijt} = Z_i'\beta + a_{ijt} + u_{it}$$

[37] This simplification is made primarily for computational purpose. In the sample, about 15% and 25% of the workers ever give two distinct answers to questions on marital status and whether being hourly paid respectively. SIPP contains topical modules which provide information on marital history of the household. In principle, these information can be used to trace X_{it} over time. If assuming that marriage and employed by hourly paid jobs are exogenous and predetermined, one could solve the dynamic programming problem for each worker given his observed X_{it} and expected X_{it} beyond the observation period. This would dramatically increase the computation burden, as opposed to solving the model for each type of worker holding X_i fixed over life. A more difficult question is to allow marriage and choosing jobs paid by hour to be endogenously determined, which I leave for future research.

and the error terms evolve according to the following stochastic processes:

$$a_{ijt} = \begin{cases} a_{ijt-1} + c_i + \eta_{ijt} \equiv a^l_{ijt}, & \text{if } M_t = 0 \\ a^o_{ij't}, & \text{if } M_t = 1 \end{cases}$$

$$u_{it} = u_{it-1} + \delta_i + \zeta_{it}$$

where as previously defined, $a^o_{ij't}$ is the offered match value; $a^l_{ij't}$ denotes latent match level wage in period t prior to selection, and M_{it} is the observed mobility indicator, which equals to one when there is an acceptable offer. Without switching cost, Proposition 1 implies that job decision rules can be formulated as:

$$J^*_{it} = a^o_{ij't} - a^l_{ijt} \tag{9}$$

$$J_{it} = \begin{cases} 1 \ if \ J^*_{it} > 0 \\ 0 \ elsewhere \end{cases} \tag{10}$$

$$O_{it} = \begin{cases} 1 \ with \ probility = \lambda^e \\ 0 \ with \ probility = 1 - \lambda^e \end{cases} \tag{11}$$

$$M_{it} = J_{it} \times O_{it} \tag{12}$$

where J^*_{it} is the offer acceptance rule (choice); O_{it} defines the outcome of a trivial offer arrival process (chance) which is common across workers and independent to J_{it}. J^*_{it} is defined only over $O_{it} = 1$. Neither O_{it} nor J_{it} is observed by the econometrician; only the single indicator M_{it} is observed. If $M_{it} = 0$, new match level wage in period t is a^l_{ijt}; if $M_{it} = 1$, the new match becomes $a^o_{ij't}$. While job offers $a^o_{ij't}$ are independent draws from the offer distribution, accepted offers are not. Indeed, accepted matches $a_{ij't}$ are draws of $a^o_{ij't}$ from a truncated normal distribution such that $a^o_{ij't} > a^l_{ijt}$, so the lower truncation point is a function of labor market histories. The empirical model without switching cost is an exact representation of the on-the-job search model. Evaluating the selection equation does not require one to solve the value function, and the computation burden is equivalent to solving a static model in every period.

As discussed previously, with non-zero switching cost, the only thing that is different is the offer acceptance rule:

$$\begin{aligned} J^*_{it} &= V^e_t(S(j',t)^a, M_t = 1) - V^e_t(S(j,t)^a, M_t = 0) \\ &= V^e_t(S(j',t)^a, M_t = 0) - V^e_t(S(j,t)^a, M_t = 0) - k_{it} \end{aligned} \quad (13)$$

Unlike the zero-switching cost model, here one needs to solve the value function for every possible combination of the state variables. The state variable vector contains $\{X_i, a_{ijt}, c_i, \kappa_{it}\}$. The computational difficulty here is that a_{ijt}, c_i are continuously distributed and serially correlated unobserved state variables. State variable c_i represents unobserved heterogeneity to the econometrician although each worker is assumed to know his person-specific value. This implies that for estimation purpose we need to solve the value function for different value of c_i. Moreover,to solve the finite horizon dynamic programming problem at t, we need to know the value function at $t+1$ for every possible combination of state variables a_{ijt+1} that may arise conditional on a_{ijt}. As t increases, the problem quickly becomes intractable[38]. Appendix B describes the solution method in detail. The method uses Monte Carlo integration and interpolation method to approximate the value function.

I estimate both empirical models–the model without switching cost and the model imposing it. The preferred model is the model imposing job-switching cost. As we shall see the results demonstrate that non-wage factors are very important determinants of job mobility decisions.

5.2 Identification

Coefficients (β) on observable vector Z_i is identified by the initial wage assumption. Since wage residual observed in the first period of work life is assumed exogenous (no selection takes place prior to the beginning of work life), OLS regression of observed wages in the first period work life produces consistent estimates of β.

The foregoing discussion demonstrates that the search model implements two selection equations: one is the trivial and exogenous offer arrival process which does not depend on any covariates, and the other is the job selection rule. In the full model with switching cost, the job selection rule can be thought as a reduced-form equation on X_i which is analogous to the choice equation in the classic Heckman

[38]This is known as the "curse of dimensionality" problem. See Aguirregabiria and Mira (2009) and the reference therein.

selection models. Therefore the switching cost parameters Υ is identified by exclusion restrictions. The instruments are marital status and whether employed by an hourly-paid job which affect the job selection equation but not the wage equation.

Our wage process decomposes wage residuals into two parallel processes: one at person level evolving independently of job mobility, one at worker-firm level which determines job mobility. This is an important identifying restriction to separate match component from person component in observed wage residuals. I partition the rest of the parameters into two sub-vectors: $\Theta^m = \{\lambda^e, \sigma^2_{a_0}, \sigma^2_\eta, \sigma^2_c, \mu_c\}$ and $\Theta^u = \{\sigma^2_{u_0}, \sigma^2_\zeta, \sigma^2_v, \mu_\delta\}$. The former vector determines both wage and mobility histories; the latter parameter vector only determines observed wages and is independent of mobility.

Appendix C derives analytical expressions of the moment conditions used for the first two periods, and describes in detail how each of the parameters in Θ^m and Θ^u could be identified. A more intuitive argument is developed here.

First, Θ^m is identified by persistence of mobility within person histories, correlation between mobility and wage histories, and distributional assumptions on match level wage process. A widely recognized difficulty in estimating search models is that rejected offers (wage offers below the reservation wage) are unobserved. Hence the normality assumption on the offer distribution is necessary to recover the mass below the reservation wage (Flinn and Heckman, 1982). Analogously, extremely bad shocks to a_{ijt} and extremely low c_i are not observed if workers are able to switch jobs very quickly. Distributional assumption on the shocks and random growth factor is essential in evaluating the mass at the bottom of the distribution.

Persistence of mobility decisions within worker histories identifies random growth factor c_i. Conditional on observed state variables, persistent job-job transitions over time imply that the worker has a small c_i. A simulation exercise conducted in Appendix C shows that σ^2_c can be identified from autocovariances of mobility at sufficient long lags. The structural search model implies a correlation between lagged wages and current and future mobility decisions. Conditional on observed state variables, changes in this correlation within worker histories over time identify match level shock. Essentially, what separates match level shock apart from person-level shock is that the former correlates with current and future mobility decisions and the latter does not.

Next, given Θ^m, Θ^u can be identified using the variance and covariance of wage residuals, a standard in the literature. Random growth factor δ_i is identified from the nonlinearity of covariances in labor market age, because it implies that the variance of wage residuals is quadratically increasing with labor market age. Transitory shocks are identified from the variance of wage residuals since they are assumed i.i.d and hence do not affect covariances of wages. Initial heterogeneity σ^2_{u0} is identified from variance of wages at the beginning of work life.

5.3 The initial condition problem

In the model a worker begins his first job with a random draw from the offer distribution. Therefore wages in the first period of work life are exogenous. Observed wages in subsequent periods are as a result of selection and therefore are endogenous.

Since SIPP is a short-panel, it's typical that workers have left-censored job histories when they are observed in the first wave of SIPP. Therefore for workers with left-censored job histories, their observed wages are endogenous and we have an initial condition problem (Heckman, 1981). Recall from the Data section that there is information on the starting date of worker's present job when he is first sampled, and this information is used to select a sample of workers whose complete job histories are known from the beginning of work life. Let us define p ($p = 1, ..., P$) as the observation period for a worker in SIPP, and let τ represent the elapsed job duration in the first observation period ($p = 1$). Since we know that in our sample a worker's present job is his first job, p and τ together maps into a unique work life period t: $p + \tau = t$.

The initial condition problem can be solved by simulating the model starting from the beginning of life cycle and examining the desired statistics conditional on worker's past mobility choice. Specifically, we observe a worker's mobility choices starting from the beginning of work life: $M_0 = M_1 = ... = M_\tau = 0$. Starting from work age $\tau + 1$ through $\tau + P$, we observe both his mobility choice and wage information. Recognizing that match value in initial life cycle period is an exogenous random draw, we can simulate job mobility and wage histories from the beginning of work life to $\tau + P$. Simulated statistic (e.g. mean wages) in period $\tau + p$ conditional on $M_0 = M_1 = ... = M_\tau = 0$ is a consistent estimator for the observed statistic in observation period p.[39]

[39] If the worker's present job (at the time he is sampled) is not his first job, this approach is also valid provided we know exactly when the job change occurs. SIPP does not contain this information. In other words, the key is we need to observe worker's complete pre-sample job mobility history.

5.4 MSM estimation

The full model is parsimoniously characterized in terms of the parameter vector[40]

$$\Theta = (\beta, \lambda^e, \sigma_\delta^2, \sigma_c^2, \sigma_{u_0}^2, \sigma_{a_0}^2, \sigma_\eta^2, \sigma_\zeta^2, \sigma_\kappa^2, \sigma_v^2, \mu_c, \mu_\delta, \Upsilon) \tag{14}$$

Due to computational complexity, it is difficult to accurately estimate all elements of Θ in one step. I employ a two-stage estimation procedure. In the first stage of the estimation, I select workers whose initial wage on their first job is observed[41]. As discussed previously, regressing it on observed personal characteristic Z yields a consistent estimator of β–the coefficient vector on Z. Vector Z includes a constant, education dummies, race, a polynomial in calendar age and interactions between age and education dummies. *Age* here captures the effect of potential labor market experience on worker's initial wage. Consistent with majority of findings from Mincerian earning regressions, the R^2 in the first stage regression is low (0.17), leaving the bulk of initial wage variations to initial unobserved heterogeneity in match- and person-level wage component.

Given a consistent estimate of β, I obtain predicted log wage residuals r_{ip} for each worker in each observation period in the sample. When calculating predicted residuals for each worker, *Age* is held fixed at the calendar age when he enters the labor market. By doing so, the age profile of wage residuals will be accounted for through mechanism of the model: through mean return to tenure (μ_c), return to experience (μ_δ) and worker's selection into better jobs. For the remaining analysis I work with log wage residuals denoted by r_{ip}.

Remaining parameter vector, denoted by θ, is estimated by MSM. For each worker in the sample, we observe a vector of mobility choices M_p and a vector of wage residuals r_p. From these two vectors, we can derive the empirical moments $s_i(M_{p_1}, r_{p_1}, M_{p_2}, r_{p_2})$ for any two observation period p_1 and p_2 such that $1 \leq p_1 \leq p_2 \leq P$:

$$\begin{aligned} s_i(M_{p_1}, r_{p_1}, M_{p_2}, r_{p_2}) =& (M_{ip_2}, r_{ip_2}, (r_{ip_2} - \overline{r_{p_2}})(M_{ip_1} - \overline{M_{p_1}}), (M_{ip_2} - \overline{M_{p_2}})(r_{ip_1} - \overline{r_{p_1}}) \\ & (r_{ip_2} - \overline{r_{p_2}})(r_{ip_1} - \overline{r_{p_1}}), (M_{ip_2} - \overline{M_{p_2}})(M_{ip_1} - \overline{M_{p_1}}))' \end{aligned} \tag{15}$$

[40]The discount factor Γ is held fixed at 0.97.

[41]672 workers satisfy this criteria.

where $\overline{r_p}$ is the population average of r_{ip} in period p; M_{ip} denotes binary mobility choice and $\overline{M_p}$ is the population average of M_{ip} in period p. Averaging $s_i(M_{p_1}, r_{p_1}, M_{p_2}, r_{p_2})$ over the sample, the empirical moments we are fitting are essentially the mean, variance and covariance of wage and mobility in any two observation periods.

The empirical model to be estimated is:

$$s_i(M_{p_1}, r_{p_1}, M_{p_2}, r_{p_2}) = f(\theta; X_i, \tau_i, p_1, p_2) + \varepsilon_i \tag{16}$$

Function f is the expected value of $s_i(M_{p_1}, r_{p_1}, M_{p_2}, r_{p_2})$ as implied from the model. It's important to note that the predicted moments f depends on τ_i (elapsed duration of the first job at $p = 1$), because of the left-censoring problem in the sample. τ_i, p_1 and p_2 map into two unique life periods t_1 and t_2. Conditional on observed state variables, the theoretical moments is a function of life period t_1 and t_2 conditioning on that $M_0 = M_1 = ... = M_{\tau_i} = 0$.

The function f is complicated to compute analytically, because in the presence of endogenous selection on the match process, the distribution of the state variables at any given life period, $F(s(j,t); \theta, X_i, Z_i, \tau_i)$, is difficult to evaluate. I choose to approximate it by its simulated counterpart:

$$\hat{f}(\theta; X_i, \tau_i, p_1, p_2) = \frac{1}{S}\sum_{s=1}^{S} f(\theta; \hat{\nu_s}, X_i, \tau_i, p_1, p_2) \rightarrow f(\theta; X_i, \tau_i, p_1, p_2) \tag{17}$$

where after taking the mean of the simulated sample, $\hat{f}(\theta; X_i, \tau_i, p_1, p_2)$ becomes the simulated moment vector containing the mean, and variance and covariance of earnings and mobility at two work life period t_1 and t_2 which $\{\tau_i, p_1, p_2\}$ map into. $\hat{f}(\theta; X_i, \tau_i, p_1, p_2)$ converges to $f(\theta; X_i, \tau_i, p_1, p_2)$ as the number of simulations S becomes large. $\{\hat{\nu_s}\}_{s=1}^{s=S}$ is a sequence of random variables that are identically and independently distributed. It consists of sequence of job offer draws a^o, shocks to match component η and shocks to switching cost from all periods, and a random variable person-specific tenure effect c_i [42]. With $\hat{\nu}$, the model is able to simulate S job histories for each individual[43]. Person component

[42] These normally distributed random variables are constructed through the inversion method. That is, first draw a vector of random variables z from a uniform (0,1) distribution and evaluating the inverse of cumulative normal distribution $F^{-1}(z)$ yields a vector of normally distributed random variables. The uniform draws z are held fixed and independent of model parameters. This guarantees that MSM objective function varies only with respect to changes in parameters of interest.

[43] Vector $\hat{\nu}$ is held fixed across individuals of the same type because its distribution does not depend on i. A usual caveat to this frequency-type simulator is that the mobility function is non-smooth in the parameters, introducing difficulties for gradient-based optimization method. I smooth M_{it} by $\Phi(\frac{J_{it}^*}{h})$, where Φ is the standard normal cumulative distribution function and h is a smoothing parameter. When $h \rightarrow 0$, the approximation converges to the frequency simulator.

variables are additive to match component and they do not affect the mobility rules. Therefore person-level shocks are not simulated and they enter in $\hat{f}$ with an analytical expression. For example, one of the theoretical moments is $var(r_{it})$ consisting of a linear combination of $var(u_{it})$ and $var(a_{ijt})$. As person-level wage u_{it} is independent of job mobility decision, the former can be expressed as function of model parameters: $var(u_{it}) = \sigma^2_{u0} + t^2\sigma^2_{\delta} + t\sigma^2_{\eta}$. The latter, however, can only be evaluated using Monte Carlo simulations.

Assume we have a balanced panel data at hand for notational convenience. Taking sample averages, LHS of equation (16) becomes the mean, variance and covariance of mobility and wage residuals between any two observation periods in the sample:

$$(E(M_{ip_2}), E(r_{ip_2}), cov(r_{ip_1}, r_{ip_2}), cov(M_{ip_1}, M_{ip_2}), cov(r_{ip_1}, M_{ip_2}), cov(M_{ip_1}, r_{ip_2}))'$$

The vector of simulated moments for any given two observation period is:

$$\mathbf{g}(\theta; p_1, p_2) = \mathbf{s}(M_{p_1}, r_{p_1}, M_{p_2}, r_{p_2}) - \frac{1}{N}\sum_{i=1}^{N} \hat{f}(\theta; X_i\tau_i, p_1, p_2) \tag{18}$$

where N is the number of worker in the panel, $\mathbf{s}$ is the sample average of $s_i(M_{p_1}, r_{p_1}, M_{p_2}, r_{p_2})$. Since we calculate f for every worker that we observe at p_1 and p_2, effectively, the simulated population has the same distribution of X, Z, τ as in the observed sample.

Let $\mathbf{g}(\theta)$ be a vector consisting $\mathbf{g}(\theta; p_1, p_2)$ at all possible combinations of p_1 and p_2. The size of vector $\mathbf{g}(\theta)$ is $M \times 1$. The total number of moments is $M = (P + 1)(2P - 1)$. I choose $P = 8$, leading to a total of $M = 135$ moments used[44]. The goal of the second stage estimation is to find θ which minimizes:

$$\mathbf{g}(\theta)'\mathbf{W}\mathbf{g}(\theta) \tag{19}$$

where $\mathbf{W}$ is a M by M weighting matrix. The weighting matrix is chosen as a diagonal matrix such that

[44] Beyond 8 sample periods, the sample size is not large enough to have reliable estimates of empirical moments.

$\mathbf{W} = A^{-1}$. A is a diagonal matrix whose elements on the main diagonal is given by

$$A_{kk} = \frac{1}{N}\sum_{i=1}^{N}(\mathbf{s}_i - \mathbf{s})(\mathbf{s}_i - \mathbf{s})'$$

Therefore the main diagonal of $\mathbf{W}$ contains the inverse of the variance of corresponding elements in $\mathbf{s}$. Given the set of moments, this diagonally-weighted minimum distance estimator is more efficient than the equally-weighted estimator where W is an identity matrix. Intuitively, this weighting matrix allows us to adjust the moment conditions such hat they all enter the objective function as being roughly similar in scale. This is particularly important given my moment choice because the covariance between wage and mobility is much smaller than the variability of wage[45]. It also avoids the large small sample bias if the optimal weighting matrix were used, which are primarily related to the off-diagonal elements in the optimal weight matrix (Altonji and Segal, 1996).

For the model without switching cost, the selection equation does not depend on observables X_i, meaning that the simulated moment can be written as $\hat{f}(\theta; \tau_i, p_1, p_2)$. In this case, I simulate $S = 5000$ elements of c_i(return to tenure), and $S = 5000$ vectors of job offer and worker-firm match shock. Both the job offer and match shock vector have length equal to 40, the maximum length of labor market experience observed for the worker. Given these draws, I obtain S simulated mobility and wage residuals for the first 40 periods as implied from the model. For the model with switching cost, the difference is that the simulated moment is a function of observables X. Therefore the simulated mobility and wage histories are type specific (i.e. depends on X). To ease computational burden when approximating the value function, the distribution of c_i is discretized into Q points: $\{c_i^q\}_{q=1}^{Q}$, each carrying the same probability mass. For each type of X and each type of c_i, I simulate $S_q = 500$ mobility and wage histories since the beginning of work life. Given X, the total number of simulated job histories is equal to $S_q \times Q$.

For both model specifications, the time when researchers begin to observe a worker's wage depends on τ_i. For example, suppose $\tau_i = x_0$ for a given worker, and a subset of S simulated job histories (denote the set by A) satisfy $M_0 = M_1 = ... = M_{x_0} = 0$. For this particular worker, the simulated moment $\hat{f}$ is

[45] I also estimated the model using an identity weighting matrix, which is equivalent to minimizing the sum of squared residuals $\sum_{i=1}^{N}\varepsilon_i^2$. The estimated match heterogeneity and offer arrival rates are severely downward biased, although the rest of the parameters are similar. The full results are available upon request.

then

$$\frac{1}{S_{x_0}} \sum_{s \in A} f(\theta; \hat{\nu}_s, x_0, X_i, p_1, p_2) \tag{20}$$

where S_{x_0} is the number of simulated job histories that are in set A [46].

6 Estimation Results

Estimated parameters are presented in Table 6 [47]. The first and second column reports estimates for the model with and without switching cost respectively. In both specifications, worker-firm match level wage risk (σ_η^2) is more than two orders larger than person-level wage risk (σ_ζ^2). Wage risk at worker-firm match level appears to be the predominant risk facing employed workers. It implies that on-the-job search could potentially insure a huge fraction of wage risk. Initial individual heterogeneity is much larger than initial match heterogeneity, suggesting that including the individual wage component is essential to match both the extent of job-job transitions and the associated dispersion in wages. This is not completely surprising. Bils, Chang, Kim, and Hall (2009) and Hornstein, Krusell, and Violante (2007), show that match heterogeneity alone is insufficient to produce both realistic wage dispersion and unemployment fluctuations at the same time. Variance of measurement errors in wage is large, which coincides with previous discussion that measurement errors are responsible for substantial wage variations.

Comparing the first and second column, we find that the estimated initial match heterogeneity and offer arrival rate is much smaller in the switching cost model than in the model without switching cost. With switching cost, unobserved non-wage factors have impacts on the job selection equation, which would presumably drives down the variation of wage parameters. Interesting, the variance of match shocks remains large even when non-wage shocks are allowed to influence job mobility. Turning to the switching cost parameters, we find that the magnitude of switching cost is moderate, particulary for workers who did not go to college, who are not married and paid by salary. The magnitude of estimated $\gamma^{constant}$ is more than one-third of the mean log wage in the first period of life.

[46] This is the crude accept-reject method. I constrain S_{x_0} to be bounded below (minimum of 2% of total number of simulations) to ensure that S_{x_0} is also large.

[47] Standard errors will be provided by bootstrap, which is on-going work.

What happens if shocks to worker-firm match is ignored? Suppose matches are constant during the job tenure and worker's mobility choice is solely based on the value of initial match, which has been the assumption made in Low, Meghir, and Pistaferri (2009) and Altonji, Smith, and Vidangos (2009). Then we see a large increase in the estimated variance of permanent shock(column 3). A large proportion of wage fluctuations that are in fact specific to a worker-firm match has been identified as permanent shocks that will persist across all jobs. I also estimate a canonical wage process neglecting worker's selection between jobs (column 4)[48]. This has been a standard in estimating wage uncertainty in labor and macroeconomics literature. If we crudely attribute the sum of σ_ζ^2 and σ_η^2 to true permanent wage risk prior to job mobility, then the true permanent uncertainty is at least 80% higher than the permanent variance typically identified from an exogenous wage process (column 4). The true permanent uncertainty is even higher if the search model incorporates switching cost. This is because switching cost adds more frictions and inefficiency to the labor market, and hence there must be larger variations in the match-level shock in order to match the observed mobility patterns from data.

Some other estimated parameters are also of interest. The model presented in this paper contains heterogenous return to tenure, and permanent match-specific shock affecting mobility behavior. All these features are absent in reduced-form estimation of return to tenure[49]. Estimation from the structural model shows that the point estimate of return to tenure (μ_c) is about -0.4% per period (four month) and the estimated return to experience (μ_δ) is 1.2% (column 2). Surprisingly, match quality (or job-specific human capital) is decreasing on average at 2% per annum. The negative μ_c coincides with Nagypal (2005), who shows that one needs to have a decreasing value of match over the job tenure in order to match the high rate of job-job transitions in the data. Our story is similar here: if there is no depreciation in job-specific skills (i.e. μ_c is positive), it implies a quick decline in the probability of moving over time which is inconsistent to the high rate of job-job transitions we observe even for senior workers. Figure 6 shows the distribution of accepted matches in different horizons using the estimated parameters without switch cost. Even though mean return to tenure is negative, selection effect alone

[48] Since wage is assumed exogenous (no selection between jobs), the first stage regression is run using observed wages over all periods on personal characteristics including labor market experience. Transitory shocks are i.i.d although this assumption can be relaxed. The weighting matrix is set as an identity matrix since only moments on variance and covariance of wages are used.

[49] See Altonji and Williams (2005) for a reassessment of this literature. In a reduced-form estimation, any shock to match component is assumed transitory and therefore does not relate to turnover behavior. Also, if return to tenure is heterogenous, on-the-job search implies that workers whose return is low tend to switch jobs at a faster rate, generating a positive relation to observed tenure. This is likely to produce a positive source of bias to existing estimators.

is able to generate sufficient match improvement over time.

To evaluate the fit of the model, I simulate 20 careers for each worker in the sample using the parameter estimates for the switching cost model. Therefore I simulate a total of 24,220 careers and the simulated population has the same distribution of observed characteristics X and Z. I then truncate the careers according to the empirical distribution of left-censored job spells τ. The final simulated sample contains 8 observation periods, whose joint distribution of X,Z and τ matches the SIPP sample. Next, I run the wage and mobility regression on the simulated sample and compare the regression relationship between wage and mobility with those of the estimates from SIPP (Table 4). The estimated coefficients (column b) are very close to the estimates from SIPP. The only difference is the coefficient on one-period lagged mobility in the wage regression, where the model implies a negative correlation between lagged mobility and current wage. Overall I conclude that the model is able to match closely the dynamic relationship between job mobility and wage in the SIPP sample.

7 Implications of the Model

7.1 Life-cycle Wage Growth and Wage Inequality

This section argues that job-selection effect is the main drive to life-cycle wage growth and wage inequality. Using the estimated parameters (column 2 of Table 6), I simulate the wage histories for 2500 workers of a given type X_i. I then decompose the mean and the variance of simulated wages over the first 40 periods of life cycle. The primary interest is the contribution from match component and individual component of wages overtime. The left panel of Figure 7 examines the experience profile of mean wages. The growth in $E(u_t)$ is due to the positive experience effect, while the growth in $E(a_t)$ is entirely due to job selection since the return to tenure is negative. The selection effect also explains the concavity of the experience-profile, if the model is simulated long enough, as the extent of job-job transitions decreases with experience.

The right panel of Figure 7 decomposes the experience profile of wage inequality. At the beginning of life, almost all wage inequality is from variations in individual heterogeneity. As labor market experience grows, the contribution from worker-firm match quickly rises because of permanent match shocks, job-job transitions and heterogeneous return to tenure. In 10 years since the beginning of life, match variation is about the same magnitude as individual wage variation. Notice that measurement error plays a significant role in explaining cross-sectional wage inequality throughout life.

7.2 Insurance Value of On-the-job Search

In this section, I quantify the importance of on-the-job search as a channel to insure match-level wage shock for workers in the labor market. This discussion is primarily based on our preferred model–the model with job switching cost. I present three measures of insurance targeting different moments of the model.

The first measure is to evaluate the difference between discounted expected life-time utility if job mobility is allowed and its counterpart if no job-job transition is allowed. Mathematically, the value of insurance is defined as

$$\Delta V = V_0^e(S(j,0)) - V_t^e(S(j,0); \lambda^e = 0) \tag{21}$$

where $V_t^e(S(j,0); \lambda^e = 0)$ denotes the value function at the beginning of life when there is no external job offers throughout the work life. Figure 7 plots ΔV against a_0 for different types of workers. The insurance value decreases monotonically with initial match. Conditional on a_0, on-the-job search is a more valuable channel to insure match-level shocks for workers whose switching cost is low and for workers with smaller return to tenure. The life-time utility gain is also higher if match level risk is larger.

Recall that a_{ijt}^l is the latent match in period t. The second measure of how well people could self-insure latent shocks through job mobility is:

$$E(a_{ijt} - a_{ijt}^l | \eta_{it} < 0) = E(a_{ij't(0)} - a_{ijt}^l | \eta_{it} < 0, M_{it} = 1) P(M_{it} = 1 | \eta_{it} < 0) \tag{22}$$

where as previously defined, $a_{ijt}^l = a_{ijt-1} + c_i + \eta_{it}$. The equation holds because $a_{ijt} = a_{ijt}^l$ whenever $M_{it} = 0$. The LHS of equation (22) is then normalized by a constant equal to $E(\eta_{it} | \eta_{it} < 0)$. So it measures on average how much match value (as a ratio to the magnitude of negative match shock) people are able to recover immediately following a negative match level wage shock.

To highlight the implication of switching cost to the value of self-insurance, I calculate this insurance value under both specifications of the model. Panel 1 of Figure 8 presents this simulated statistic for 40 life cycle periods. Let us first focus on the prediction from no switch cost model ($k = 0$). Not surprisingly, as people's labor market age grows, the ability to recover from a negative match shock declines. For a worker one year into the labor market, he is expected to fully self-insure against negative match-level shocks. Five years after he enters the labor market, this number drops to below 50%. From equation (22), we know that two factors may contribute to the decline: the probability of locating an acceptable offer and the expected wage gains conditional on moving. Panel 2 of Figure 8 plots $E(a_{ij't(0)} - a^l_{ijt}|\eta_{it} < 0, M_{it} = 1)$ and panel 3 presents the pattern for the predicted probability of moving conditional on bad match shocks. Following a bad match shock, the probability of moving is declining over time (panel 3). As worker's match value accumulates, good offers are harder to find. Conditioning on job change, the expected gain from moving is also decreasing although it levels off to a lower level quickly over time (panel 2).

If there is switching cost during job-job transitions, the implication to insurance is somewhat different. Intuitively, we should expect the insurance value of job-job transition to be less, because worker sets a higher reservation match and is effectively less "responsive" to not-so-bad match shocks. As expected, the mean match of accepted offers are higher (panel 2) and the probability of moving is smaller (panel 3). On average, the model assuming switch cost predicts that workers are less self-insured against match shocks through job mobility: less than 45% the match shocks are insured and the number decreases as experiences increases. This comparison illustrates the importance of incorporating switching cost in the model: without switching cost, the insurance value of on-the-job search would be over-stated.

The third method to quantify the insurance value of on-the-job search is to analyze how quickly a worker is able to recover from a negative match shock. The idea is to look at the number of periods a worker takes to improve his match quality back to the pre-shock level. The shorter the expected time is, the better the worker is self-insured. Given the estimated parameters, I simulate 100 periods of labor market histories for 10,000 workers. Suppose there is a one standard deviation negative match shock for workers of labor market age t, then for each worker, I calculate the time it takes before his match exceeds the pre-shock level. The distribution of this recovery time is presented in table 7 [50]. Overall, the no-switch-cost model (upper panel of Table 7) predicts much shorter recovery time than

[50]Note since I simulate a fixed number of periods, for workers who never recovers from a bad shock within the periods of simulation, their recovery time would be right-censored. For this reason I present percentiles of the recovery time (rather than the mean).

those predicted from the switch cost model (lower panel of Table 7). For both model, the recovery time is increasing with labor market experiences, although the rise is more pronounced from the model without switch cost. Again, switch cost implies that workers are willing to wait longer for an offer that would compensate for the cost of moving. For workers who are married, have children and own a house, the median recovery time from a negative match shock is 1.7 years. In contrast, for the same worker suffering from the same shock, he would have to wait for more than 33 years if job-job transitions were disallowed. Therefore, the insurance value of on-the-job search against match level shocks is substantial. Moreover, the insurance value is heterogeneous across workers: it's more valuable for young workers and for workers facing less switch cost.

8 Conclusion

TO BE WRITTEN.

APPENDIX

A Proof of Proposition 1 and 2

In this section I provide formal proofs to Proposition 1 and 2 in the paper. For notational convenience, I make two simplifying assumptions. First, assume switching cost is a constant k_i for every worker. In the paper, shocks to k_i is i.i.d and hence does not affect the value function except the current period utility. Second, I omit state variables c_i and k_i in the proof, leaving a_{ijt} as the only state variable in worker's problem. The value function defined here is therefore conditional on worker's type c_i and k_i.

Lemma 1. *$V_t^e(a)$ is monotonically increasing in a, for all t.*

Proof. This can be established through backward induction.

$$V_T^e(a_{ijT}) = a_{ijT}$$

which is an increasing function in a_{ijT} trivially. Now suppose $V_{t+1}^e(a_{ijt+1})$ is increasing in a_{ijt+1}. Proving that $V_t^e(a_{ijt})$ is increasing in a_{ijt} concludes the induction. Now,

$$V_t^e(a_{ijt}) = a_{ijt} + \Gamma(1-\lambda^e)E_t\left[V_{t+1}^e(a_{ijt+1})\right] + \Gamma\lambda^e E_t\left[max\ V_{t+1}^e(a_{ijt+1}), V_{t+1}^e(a_{ij't+1}) - k_i\right] \quad (1)$$

We know that

$$E_t\left[V_{t+1}^e(a_{ijt+1})\right] = \int V_{t+1}^e(a_{ijt+1})dF(a_{ijt+1}|a_{ijt})$$

By the assumptions on the match process, it's easy to see that $F(a_{ijt+1}|a_{ijt}^1)$ first-order stochastically dominates $F(a_{ijt+1}|a_{ijt}^2)$, for any $a_{ijt}^1 > a_{ijt}^2$. This implies that $\int v(k)dF(k|w^1) > \int v(k)dF(k|w^2)$ for any increasing function v. Since by assumption $V_{t+1}^e(a_{ijt+1})$ is increasing in its argument and a_{ijt+1} is increasing in a_{ijt}, $V_{t+1}^e(a_{ijt+1})$ is also increasing in a_{ijt}. Hence we have established that $E_t\left[V_{t+1}^e(a_{ijt+1})\right]$ is increasing in a_{ijt}.

Suppose $V_{t+1}^e(a_{ijt+1}) > V_{t+1}^e(a_{ij't+1}) - k_i$. From equation (1), it's easy to see that $V_t^e(a_{ijt})$ is increasing in its argument. Suppose $V_{t+1}^e(a_{ijt+1}) < V_{t+1}^e(a_{ij't+1}) - k_i$. Given $k_i \geq 0$, $a_{ij't+1}$ must be at least as large as a_{ijt+1}. Since a_{ijt+1} is increasing in a_{ijt}, $a_{ij't+1}$ must also be. Then $E_t\left[V_{t+1}^e(a_{ij't+1}) - k_i\right]$ is increasing in a_{ijt} and hence $V_t^e(a_{ijt})$ is increasing in its argument. □

Proposition 1. *If $k_i = 0$ (no job switch cost), workers switch jobs if and only if there exists an offer whose match value is larger than their current value of the match.*

Proof. The reservation match value satisfies:

$$V_t^e(a_{ijt}) = V_t^e(h_t(a_{ijt}, k_i)) \quad (2)$$

By Lemma 1, we conclude $h_t(a_{ijt}) = a_{ijt}$ for all t. □

Lemma 2. *The reservation match value $h_t(a,k)$ is monotonically increasing in a, for all t.*

Proof. The reservation match value satisfies:

$$V_t^e(a_{ijt}) = V_t^e(h_t(a_{ijt}, k_i)) - k_i$$

By the implicit function theorem[51],

$$\frac{\partial h_t(a_{ijt}, k_i)}{\partial a_{ijt}} = \frac{V_t^e(a_{ijt})'}{V_t^e(h_t(a_{ijt}, k_i))'} > 0$$

□

Lemma 3. *$V_t^e(a)'$ is monotonically increasing in a, for all t=1... T-1.*

Proof. Let $\Phi(\cdot)$ and $\phi(\cdot)$ denote cumulative and density function of the offer distribution respectively. Differentiating equation 1 w.r.t. a_{ijt}

$$\begin{aligned}
\frac{\partial V_t^e(a_{ijt})}{\partial a_{ijt}} &= 1 + \Gamma(1-\lambda^e)E_t(V_{t+1}^e(a_{ijt+1})') \\
&+ \Gamma\lambda^e E_t\left[V_{t+1}^e(a_{ijt+1})'\Phi(h_{t+1}(a_{ijt+1})) + V_{t+1}^e(a_{ijt+1})\phi(h_{t+1}(a_{ijt+1}, k_i))\frac{\partial h_{t+1}(a_{ijt+1}, k_i)}{\partial a_{ijt+1}}\right] \\
&- \Gamma\lambda^e E_t\left[(V_{t+1}^e(h_{t+1}(a_{ijt+1})) - k_i)\phi(h_{t+1}(a_{ijt+1}, k_i))\frac{\partial h_{t+1}(a_{ijt+1}, k_i)}{\partial a_{ijt+1}}\right] \\
&= 1 + \Gamma(1-\lambda^e)E_t(V_{t+1}^e(a_{ijt+1})') + \Gamma\lambda^e E_t\left[V_{t+1}^e(a_{ijt+1})'\Phi(h_{t+1}(a_{ijt+1}))\right] \qquad (3)
\end{aligned}$$

where the last step follows because by definition, $V_{t+1}^e(h_{t+1}(a_{ijt+1})) - k_i) = V_{t+1}^e(a_{ijt+1})$. From (3), we obtain

$$\begin{aligned}
\frac{\partial^2 V_t^e(a_{ijt})}{\partial a_{ijt}^2} &= \Gamma(1-\lambda^e)E_t(\frac{\partial^2 V_{t+1}^e(a_{ijt+1})}{\partial a_{ijt+1}^2}) \\
&+ \Gamma\lambda^e E_t\left[\frac{\partial^2 V_{t+1}^e(a_{ijt+1})}{\partial a_{ijt+1}^2}\Phi(h_{t+1}(a_{ijt+1}) + V_{t+1}^e(a_{ijt+1})'\phi(h_{t+1}(a_{ijt+1}, k_i))\frac{\partial h_{t+1}(a_{ijt+1}, k_i)}{\partial a_{ijt+1}}\right] \qquad (4)
\end{aligned}$$

From Lemma 1 and Lemma 2, we know the last term in equation (4) must be positive. In an backward induction argument, equation (4) essentially proves the core of the induction: if $\frac{\partial^2 V_{t+1}^e(a_{ijt+1})}{\partial a_{ijt+1}^2}$ is positive, then $\frac{\partial^2 V_t^e(a_{ijt})}{\partial a_{ijt}^2}$ must also be positive. Therefore to complete the prove, we only need to show that the claim is true in the last period. In period T, $\frac{\partial^2 V_T^e(a_{ijT})}{\partial a_{ijT}^2} = 0$. Moving one period backwards,

$$V_t^e(a_{ijT-1}) = a_{ijT-1} + \Gamma(1-\lambda^e)E_{T-1}\left[a_{ijT}\right] + \Gamma\lambda^e E_{T-1}\left[max\ a_{ijT}, a_{ij'T} - k_i\right]$$

[51] $V(a)'$ denotes partial derivative of the value function w.r.t a.

It is straightforward to show that $\frac{\partial^2 V_t^e(a_{ijt})}{\partial a_{ijt}^2} = \Gamma\lambda^e E_{T-1}(\phi(a_{ijT}+k_i)) > 0$. $\square$

So far we have established that the worker's value function is increasing convex. We are now ready to prove the second proposition.

Proposition 2. *If $k > 0$, worker's optimal strategy is to set a reservation match value $h_t(a,k)$ such that $h_t(a,k) > a$. Furthermore, for all $t = 1 \ldots T-1$,it has the following properties: (1) $0 < \frac{\partial h_t(a,k)}{\partial a} < 1$ (the second inequality implies that $h_t(a,k) - a$ is a decreasing function of a); (2) $h_t(a,k)$ is monotonically increasing in k.*

Proof. The reservation match value is defined by:

$$V_t^e(a_{ijt}) = V_t^e(h_t(a_{ijt}, k_i)) - k_i \tag{5}$$

Given $k > 0$ and that the value function is monotonically increasing, one can easily prove by contradiction that $h_t(a_{ijt}) > a_{ijt}$.

To show the first property, recall that $V_t^e(a)'$ is positive (Lemma 1) and monotonically increasing (Lemma 3). Therefore,

$$V_t^e(h_t(a_{ijt}, k_i))' > V_t^e(a_{ijt})' > 0$$
$$0 < \frac{\partial h_t(a_{ijt}, k_i)}{\partial a_{ijt}} = \frac{V_t^e(a_{ijt})'}{V_t^e(h_t(a_{ijt}, k_i))'} < 1$$

Next, we show that $h_t(a,k)$ is monotonically increasing in k. Differentiating equation (5) with respect to k, we get

$$\frac{\partial h_t(a_{ijt}, k_i)}{\partial k_i} = \frac{\frac{\partial V_t^e(a_{ijt})}{\partial k_i} + 1}{V_t^e(h_t(a_{ijt}, k_i))'}$$

We know the denominator must be positive from Lemma 1. What remains to be shown is that the nominator is also positive. We prove this by backward induction.

Let us first examine $\frac{\partial V_t^e(a_{ijt})}{\partial k_i}$ in $T-1$. It is easy to show that

$$\frac{\partial V_{T-1}^e(a_{ijT-1})}{\partial k_i} = -\Gamma\lambda^e E_{T-1}(1 - \Phi(a_{ijT} + k_i))$$

whose value lies between (-1,0). Now suppose $\frac{\partial V_{t+1}^e(a_{ijt+1})}{\partial k_i} \in (-1, 0)$. Differentiating V_t^e w.r.t k

$$\begin{aligned}\frac{\partial V_t^e(a_{ijt})}{\partial k_i} &= 1 + \Gamma(1-\lambda^e)E_t(\frac{\partial V_{t+1}^e(a_{ijt+1})}{\partial k_i}) + \Gamma\lambda^e E_t\left[\frac{\partial V_{t+1}^e(a_{ijt+1})}{\partial k_i}\Phi(h_{t+1}(a_{ijt+1}, k_i))\right] \\ &\quad + \Gamma\lambda^e E_t \int_{h_{t+1}(a_{ijt+1}, k_i)}^{\infty} \frac{\partial V_{t+1}^e(a_0)}{\partial k_i} d\Phi(a_0) - \Gamma\lambda^e E_t\left[1 - \Phi(h_{t+1}(a_{ijt+1}, k_i))\right]\end{aligned} \tag{6}$$

By the induction assumption, it's obvious that $\frac{\partial V_t^e(a_{ijt})}{\partial k_i} < 0$. Then, since we know[52]

$$\int_{h_{t+1}(a_{ijt+1},k_i)}^{\infty} \frac{\partial V_{t+1}^e(a_0)}{\partial k_i} d\Phi(a_0) > \frac{\partial V_{t+1}^e(h_{t+1}(a_{ijt+1},k_i))}{\partial k_i}(1-\Phi(h_{t+1}(a_{ijt+1},k_i)))$$

Equation (6) then simplifies to

$$\frac{\partial V_t^e(a_{ijt})}{\partial k_i} > \Gamma E_t(\frac{\partial V_{t+1}^e(a_{ijt+1})}{\partial k_i}) > -1$$

assuming the discount factor Γ is between (0,1). Therefore we have shown that for all $t = 1 \dots T-1$,

$$\frac{\partial V_t^e(a_{ijt})}{\partial k_i} + 1 > 0$$

and hence

$$\frac{\partial h_t(a_{ijt}, k_i)}{\partial k_i} > 0$$

□

B Approximating the Value Function

TO BE WRITTEN Solve the model for T=40 periods (13 years); Terminal value function V41: assume job mobility ceases and no wage uncertainty from t=41 through end of life (100 periods).

C Identification of the Wage Process: Further Discussions

In this section I derive analytical forms for moment conditions given in the paper. For the purpose of illustration, I make two simplifying assumption. First, assume that complete wage and mobility histories are observed from the beginning of life (period 0) up to period T. Second, I only discuss the model where there is no switch cost, since parameter vector Υ can be identified from exclusion restrictions. The moment vector now include

$$E(M_{it_2}), E(r_{it_2}), cov(r_{it_2}, r_{it_1}|M_{it_2}), cov(M_{it_2}, M_{it_1}), cov(r_{it_2}, M_{it_1}), cov(M_{it_2}, r_{it_1}) \quad (7)$$

where $t_2 \geq t_1$.

Suppose two periods of wage and mobility data for a sample of workers are given: period 0 (when they enter the labor market) and period 1. We've assumed that wage in the initial period is exogenous, so $E(r_0) = 0, var(r_0) = \sigma_{a_0} + \sigma_{u_0} + \sigma_v$. Next, I show what can be identified given data on mobility and wages from period one.

[52] This builds on that $\frac{\partial V_t^e(a_{ijt})}{\partial k_i}$ is increasing in a, which can be proved by induction. It is easy to see that this holds for period $T-1$.

Using the notation introduced in section 5.1, let a^o be an offer, which is a draw from the normal distribution with mean zero and variance $\sigma^2_{a_0}$, and let a^l_1 denote the latent match in period one prior to mobility which equals to $a_0 + c + \eta_1$. Since a^l_1 is a linear combination of normally distributed random variables, the unconditional distribution of a^l_1 must also be: $a^l_1 \sim N(\mu_c, \sigma^2_{a^l_1})$, where $\sigma^2_{a^l_1} = \sigma^2_{a_0} + \sigma^2_\eta + \sigma^2_c$. It's also useful to observe that the joint distribution of a^l_1 and a_0 follows a bivariate normal distribution with means μ_c and zero, variances $\sigma^2_{a^l_1}$ and $\sigma^2_{a_0}$, and correlation coefficient $\rho = \frac{\sigma_{a_0}}{\sigma_{a^l_1}}$.

Consider the first moment on mobility and wages in period one:

$$
\begin{aligned}
E(M_1) &= P(M_1 = 1) = \lambda^e E_{a^l_1}\left[\Phi(-\frac{a^l_1}{\sigma_{a_0}})\right] && (8)\\
E(r_1) &= E(a_1) + E(u_1)\\
&= E(a_1|M_1 = 1)E(M_1) + E(a_1|M_1 = 0)(1 - E(M_1)) + \mu_\delta\\
&= \sigma_{a_0} E_{a^l_1}\left[\lambda(a^l_1)\right] E(M_1) + \left[\mu_c(1-\lambda^e) + \lambda^e \sigma_{a^l_1} E_{a^o}\left[\lambda(a^o)\right]\right](1 - E(M_1)) + \mu_\delta && (9)
\end{aligned}
$$

where $\lambda()$ are the inverse Mills ratio: $\lambda(a^o) = -\frac{\phi((a^o-\mu_c)/\sigma_{a^l_1})}{\Phi((a^o-\mu_c)/\sigma_{a^l_1})}$, and $\lambda(a^l_1) = \frac{\phi(\frac{a^l_1}{\sigma_{a_0}})}{1-\Phi(a^l_1/\sigma_{a_0})}$. As defined previously, Φ and ϕ are standard normal c.d.f and density function respectively.

The second moment on the covariance between mobility and wage can be written as:

$$
\begin{aligned}
cov(r_0, M_1) &= E(r_0 M_1) = E(r_0|M_1 = 1)E(M_1)\\
cov(r_1, M_1) &= E(r_1|M_1 = 1)E(M_1) - E(r_1)E(M_1)
\end{aligned}
$$

The new identification restriction imposed from these two moments are essentially $E(r_0|M_1 = 1)$ and $E(r_1|M_1 = 1)$, which can be expressed by the model parameters as:

$$
\begin{aligned}
E(r_0|M_1 = 1) &= \rho\sigma_{a_0} E_{a^o}\left[\lambda(a^o)\right] && (10)\\
E(r_1|M_1 = 1) &= \sigma_{a_0} E_{a^l_1}\left[\lambda(a^l_1)\right] + \mu_\delta && (11)
\end{aligned}
$$

where as defined above, ρ is the correlation coefficient of the bivariate normal distribution for a^l_1 and a_0.

Each of the four moments (equation (8)-(11)) is a nonlinear function of $\Theta^m = \{\lambda^e, \sigma^2_{a_0}, \sigma^2_\eta, \sigma^2_c, \mu_c\}$. It's clear that with only first period data, it's not feasible to identify Θ^m using these moments. However, the parameter set Θ^m is constant over time. With observations from multiple periods, a fast increasing number of moments are implied from the same set of parameters. With sufficient periods, these moments would over-identify all the parameters in Θ^m except for σ^2_η and σ^2_c, which I'd return to momentarily.

If there is no match-level shock and no random growth factor to wages, $a^l_1 = a_0$, and $E(a_0|M_1 = 1) = E(a_0|a_0 < a^o)$ which is the mean of the truncated job offer distribution. These relations no longer hold in light of match-level wage uncertainty. Notice that with match uncertainty the distribution of latent match in period one (a^l_1) is a mean-preserving spread of the distribution of a_0. Worker's mobility decision in period one is based on the realization from the distribution of a_1^l. Now $E(a_0|M_1 = 1) = E(a_0|a_1^l < a^o)$ becomes the mean of the truncated bivariate normal distribution. $a_0$is conditioning on a larger information set. a_0 and a_1^l are positively correlated, so the truncation of a_1^l from above would push the distribution of a_0 to the left. The degree of such push depends critically on the correlation coefficient ρ which is a function of $\sigma^2_{a_0}$, σ^2_η and σ^2_c. Given an offer from the offer distribution, the difference between $E(a_0|M_1 = 1)$ and $E(a_0|a_0 < a^o)$ provides important identification restriction to the distribution of match-level shocks.

The above discussion could in principal extend to all periods, although it would be difficult to write out analytical expressions for our purpose. For $t \geq 1$, a_t would not be normally distributed (since it's after selection) and hence the distribution of a^l_{t+1} (the latent match at the beginning of next period) is non-normal. As evidenced in Figure 4, while initial match is assumed normally distributed, the distribution of subsequent matches quickly become left-skewed as workers self-select for better jobs over time.

These first-order moments alone do not separately identify σ^2_η and σ^2_c because they are linearly additive in $\sigma^2_{a^l_t}$. Intuitively, at the mean level, random growth factor c_i can be thought as a special match level shock drawn from a given distribution except that the draw is accidentally the same for all periods. σ^2_c and σ^2_η are separately identified through moments on autocovariances of job mobility. The key argument is that long autocovariances of job mobility identifies σ^2_c. Figure C1 plots the simulated autocovariances of mobility at different lags, given three sets of combinations of σ^2_η and σ^2_c while holding the rest of the parameters fixed. While both higher σ^2_η and σ^2_c lead to an increase in the covariances of mobility across different lags, the influence of σ^2_η is decreasing with lags. Hence σ^2_c is identified from autocovariances of mobility at sufficient long lags.

The remaining parameters Θ^u are identified in a conventional way, by using moments on autocovariances of wages. The second moments on wages also impose additional restrictions on parameters related to job mobility decision and make the MSM estimator more efficient. In specific,

$$cov(r_{it}, r_{ik}) - cov(a_{it}, a_{ik}) = \sigma^2_{u_0} + tk\sigma^2_\delta + k\sigma^2_\eta, if\ k < t, \tag{12}$$

$$var(r_{it}) - var(a_{it}) = \sigma^2_{u_0} + t^2\sigma^2_\delta + t\sigma^2_\eta + \sigma^2_v \tag{13}$$

The LHS is the autocovariance of wages that are unaccounted for by the match level process. σ^2_δ and σ^2_ζ impose that the autocovariances grow nonlinearly and linearly respectively with time locations. Hence they are identified by fitting in a quadratic and linear trend on unexplained autocovariances (Guvenen, 2007). It is easy to separate variance of transitory shocks from permanent shocks here because there is no persistency in transitory shocks: σ^2_v has an additive effect on the variance but no effect on autocovariances of order one or higher. $\sigma^2_{u_0}$ is identified by subtracting σ_{a_0} from variance of wage residuals in the first period.

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Table 1: Summary Statistics, SIPP 1996 Panel

Variable	Mean	Standard Deviation
Wages	11.47	5.39
Hourly paid	0.65	0.48
Hours of work per week	43.26	8.61
Proportion of job-job transition	0.10	0.30
Elapsed job duration in the first observation period	7.74	7.37
Age	26.45	2.78
White	0.75	0.43
Some college or more	0.57	0.49
Metropolitan	0.82	0.38
Married	0.50	0.50

Note: This table reports wavely (four-month) averages. Wages are deflated using CPI-Urban (CPI=1 in 1996:1)

Table 2: Total number of job changes during the sample period (in percentages)

	Number of job changes				
	0	1	2	3	4+
quartiles of initial labor market experience					
less than 25th	31.2	29.3	21.5	10.9	7.1
25-50	46.8	29.9	15.3	6.1	1.9
50-75	60.0	23.5	11.2	4.2	1.1
more than 75th	72.1	18.9	7.6	1.0	0.3
Total	52.2	25.5	14.0	5.6	2.6

Table 3: Tobit regression of total number of job changes

married	-0.11
	(0.13)
hourly paid	0.27**
	(0.14)
white	0.10
	(0.14)
high school	-0.06
	(0.22)
at least some college	-0.12
	(0.21)
initial experience level	-0.10***
	(0.01)
Constant	0.75***
	(0.25)
Observations	1211

Note: Tobit regression of total number of job changes on observed personal characteristics. Regressors include a constant, labor market experience in the first observation period, and dummy variables of marital status, whether paid by hour and education. Asymptotic standard errors are in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 4: Dynamics of wage and job mobility

	SIPP Sample		Simulated Sample	
	(1a)	(2a)	(1b)	(2b)
Variable	$ln(w_t)$	M_t	$ln(w_t)$	M_t
$ln(w_{t-1})$	0.554	-0.091	0.505	-0.107
	(0.011)	(0.000)	(0.002)	(0.003)
$ln(w_{t-2})$	0.328	-0.018	0.387	-0.024
	(0.011)	(0.217)	(0.002)	(0.003)
M_t	0.010	-	0.002	-
	(0.009)		(0.002)	
M_{t-1}	0.037	0.127	-0.013	0.081
	(0.009)	(0.000)	(0.002)	(0.003)
M_{t-2}	-0.016	0.037	-0.021	0.061
	(0.009)	(0.002)	(0.002)	(0.003)
R^2	0.70	0.04	0.72	0.06
Observations	7266	7266	145320	145320

Note: OLS regressions of log wage and job mobility. Regressors include a constant, one and two period lagged log wage and mobility. Asymptotic standard errors are below the coefficient estimates.

Table 5: The job mobility probit

	(1)	(2)	(3)	(4)	(5)
within job wage growth in t-1	-0.202	-0.256	-0.497	-0.421	-0.601
	0.091	0.092	0.100	0.121	0.128
within job wage growth in t-2	-	-	-	-0.176	-0.472
				0.117	0.129
Job tenure in t-1	-	-0.026	-0.025	-	-0.029
		0.003	0.005		0.007
$ln(w_{t-2})$	-	-	-0.470	-	-
			0.059		
$ln(w_{t-3})$	-	-	-	-	-0.372
					0.072
experience in t-1	-	-	-0.006	-	0.001
			0.006		0.007
Observations	6381	6381	6381	4766	4766

Note: Probit model is estimated using maximum likelihood. The dependent variable is job change indicator (JC=1 if job change occurs). Regressors include a constant, one and two period lagged within job wage growth and wage levels, completed job tenure, work experience, two and three period lagged level of wage and demographic controls. Asymptotic standard errors are below the coefficient estimates.

Table 6: Estimated model parameters

	No switching cost (k=0)	With switching cost ($k \neq 0$)	Constant match	Neglect job mobility
	(1)	(2)	(3)	(4)
Wage shocks				
$\sigma_\eta^2 \times 100$	0.624	0.829	-	-
$\sigma_\zeta^2 \times 100$	0.003	0.005	0.176	0.321
σ_v^2	0.037	0.033	0.036	0.046
Random growth factor				
μ_c	-0.006	-0.004	-	-
$\sigma_c^2 \times 10000$	0.496	0.108	-	-
μ_δ	0.004	0.012	-0.002	-
$\sigma_\delta^2 \times 10000$	0.010	0.255	0.000	0.000
Heterogeneity				
$\sigma_{a_0}^2$	0.015	0.002	0.065	-
$\sigma_{u_0}^2$	0.084	0.068	0.072	0.057
Other labor market parameters				
λ^e	0.849	0.483	0.730	-
$\gamma^{constant}$	-	0.698	-	-
$\gamma^{married}$	-	-0.378	-	-
γ^{hourly}	-	-0.027	-	-
γ^{hs}	-	0.084	-	-
$\gamma^{college}$	-	-0.386	-	-
γ^{race}	-	-0.277	-	-

Table 7: Years to recover from a permanent match level shock

Prediction from model without switch cost						
	Labor market experience (years)					
quantiles	0 year	1 year	3 years	5 years	10 years	No job-job transitions
10th	0.3	0.3	0.3	0.3	0.3	0.3
25th	0.3	0.3	0.3	0.7	0.7	0.7
median	0.3	0.7	1.0	1.3	1.3	2.7
75th	1.0	1.7	2.7	3.0	3.7	> 33
90th	1.7	3.7	6.0	8.0	10.7	> 33

Prediction from model with switch cost (married, has child, house owner)						
	Labor market experience (years)					
quantiles	0 year	1 year	3 years	5 years	10 years	No job-job transitions
10th	0.3	0.3	0.3	0.3	0.3	0.3
25th	1.0	0.7	0.7	0.7	0.7	1.0
median	2.0	1.7	1.7	1.7	1.7	> 33
75th	4.0	3.7	3.7	4.0	4.3	> 33
90th	7.0	7.7	9.7	11.0	12.0	> 33

Note: For each model, the prediction is based on 10,000 simulated labor market histories of 100 periods given estimated parameters. All numbers displayed are in years.

Figure 5A: Distribution of within and between real wage growth

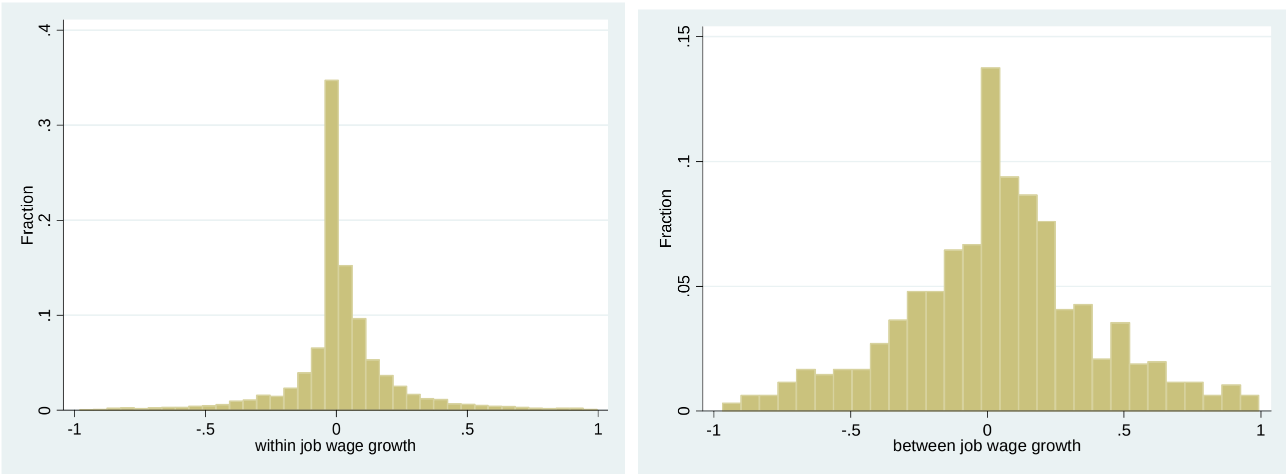


Figure 5B: Distribution of within and between nominal wage growth

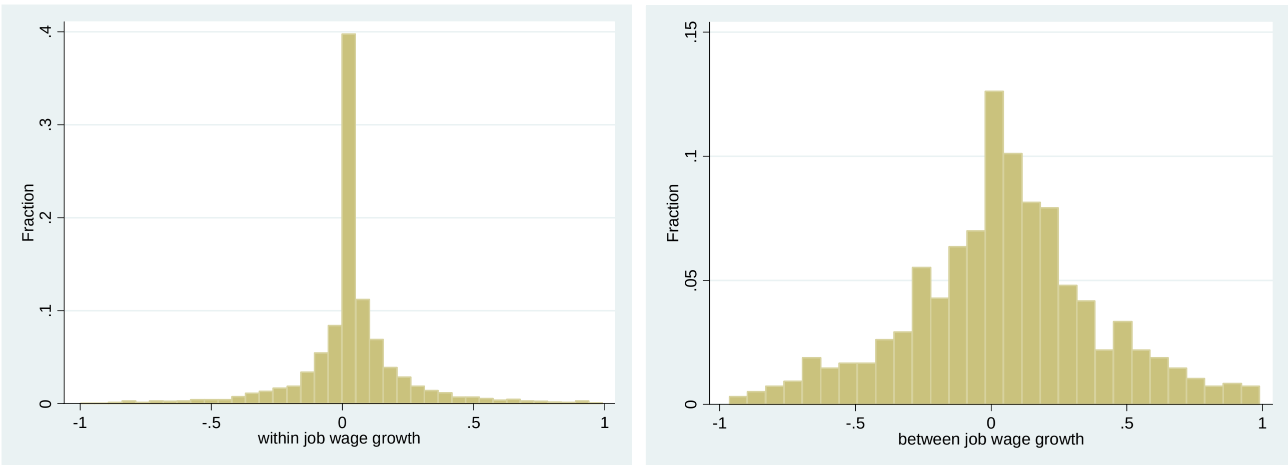
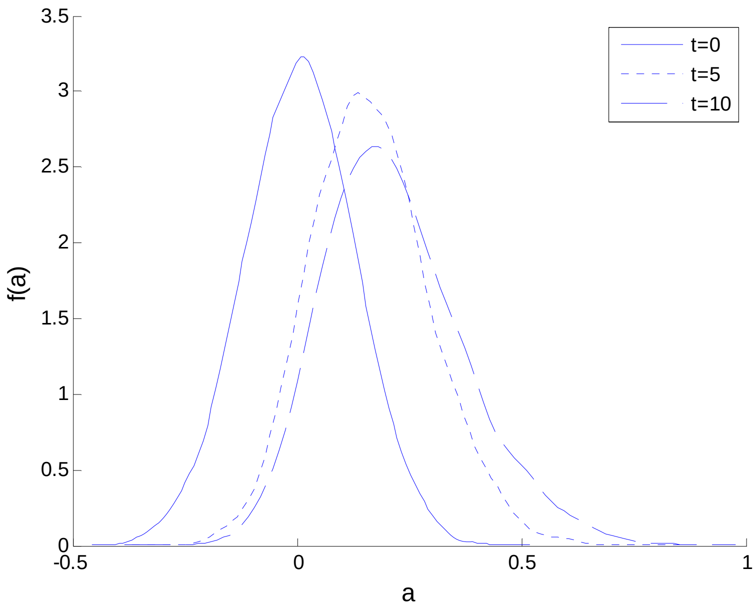


Figure 6: Distribution of accepted matches over time



Note: the distribution is generated using 5,000 simulations and then smoothed by a normal kernel. The parameter of the distribution is based upon the model without job switch cost.

Figure 7: Decomposing the experience-profile of wages

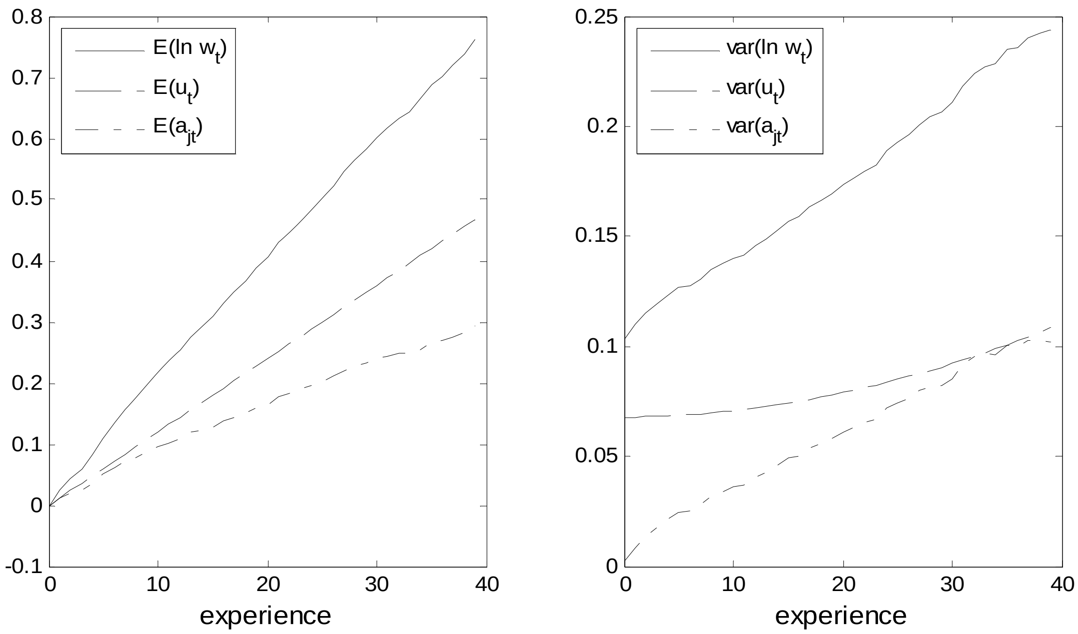


Figure 8: Insurance value of on-the-job search

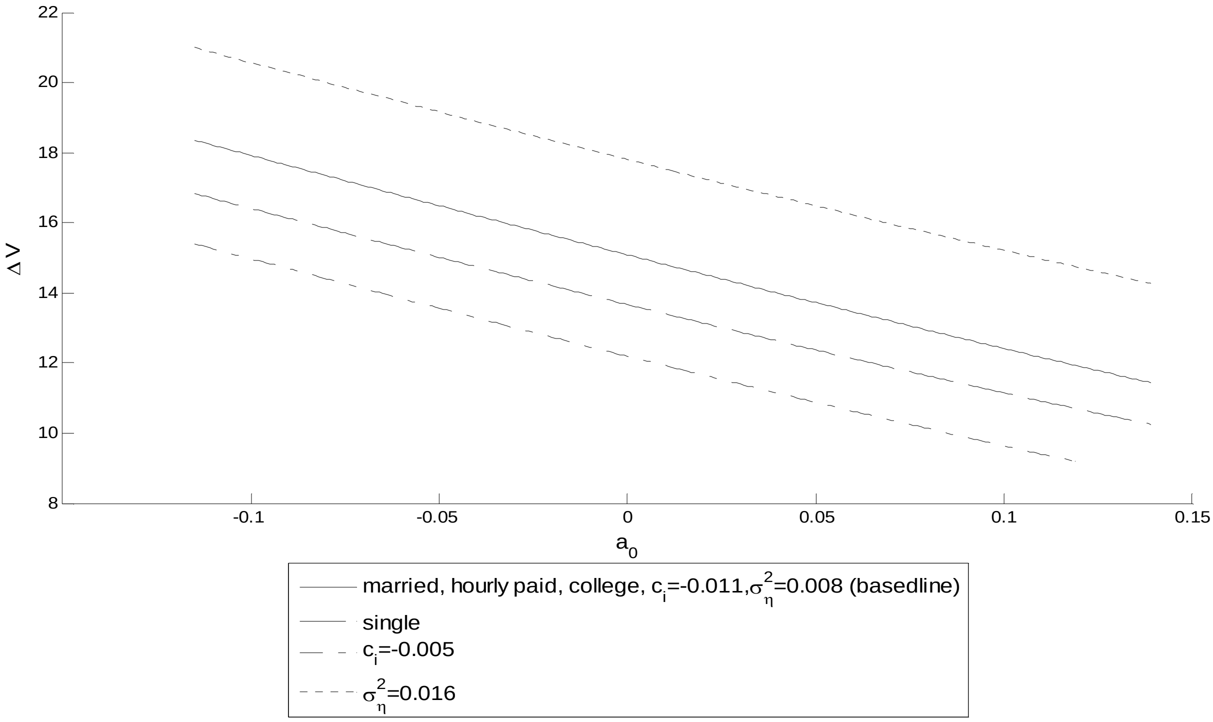


Figure 9: Predicted level of self-insure against match level shock over the life cycle

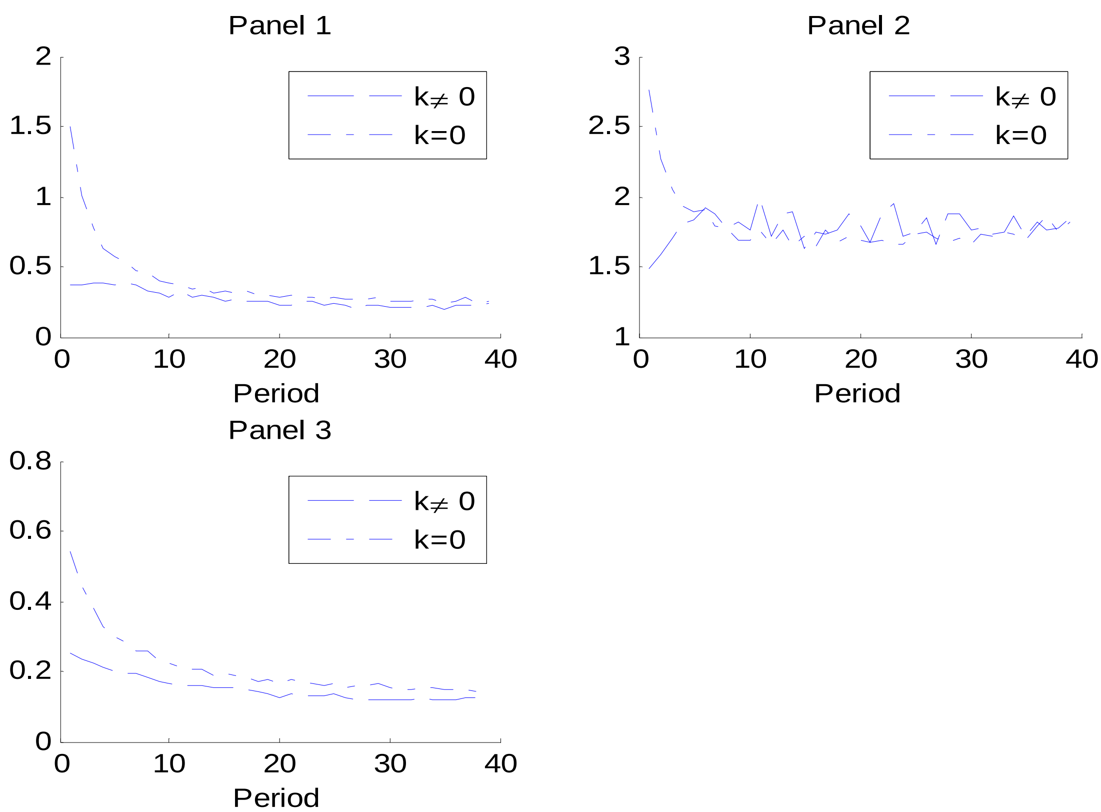
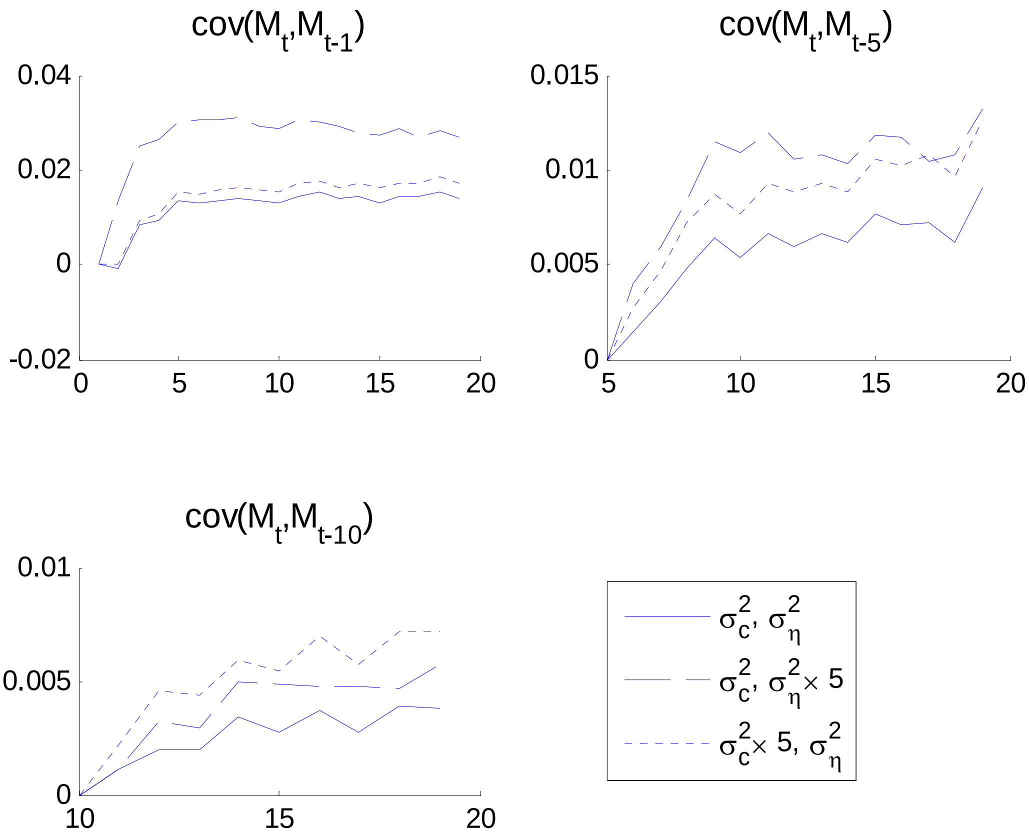


Figure C1: The effect of σ_η^2 and σ_c^2 on the autocovariance of job mobility



Note: parameters are taken from the estimates of the no-switching-cost model.