A Dynamic Analysis of Sectoral Mobility, Worker Mismatch, and the Wage-Tenure Profile*

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Abstract

A dynamic multi-sector model with net and excess mobility is developed to quantify the determinants of the canonical increasing wage-tenure profile and the negative wage gap between sector leavers and stayers at both the origin and destination sectors. The model distinguishes between three factors: sector-specific skill accumulation, sectoral-level shocks, and dynamic worker-sector mismatch shocks. The sector-specific skill premium drives the observed negative correlation between lifetime earnings and mobility. Excess mobility driven by worker-sector mismatch shocks explains nearly 20 percent of the observed wage growth for recent movers. A model featuring only dynamic worker-sector mismatch shocks still captures the salient features of the wage-tenure profile and sectoral mobility. Sectoral-level shocks have a negligible impact on the wage-tenure profile.

Keywords: Stochastic Multi-Sector Model, Excess and Net Mobility, Dynamic Sectoral Mismatch, Labor Income Shocks
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1 Introduction

Wages increasing with tenure represents a canonical result in the literature characterizing the wage-mobility relationship. This fact is typically attributed with sector-specific skill accumulation (i.e., skill premium). If indeed there exist large gains to experience, why do some workers decide to move? As Topel (1991) notes, the increasing wage-tenure profile may simply result from certain workers being more likely to have longer tenures (less likely to move) rather than any sector-specific skill premium. To understand and quantify the role played by skill accumulation in the wage-tenure profile, one must explicitly model the underlying mobility decision.

Recent work on mobility and wages (e.g., Rogerson (2005) and Kambourov and Manovskii (2008)) focuses primarily on sectoral-shock driven net mobility and sector-specific skill accumulation. Jovanovic and Moffitt (1990), however, argue that worker-sector mismatch drives most sectoral mobility. Thus, potentially all three factors contribute to the increasing wage-tenure profile: sector-specific skill accumulation, worker-mismatch, or sectoral-shifts. While some (e.g., Jovanovic and Moffitt (1990) and Moscarini (2001)) explore the effects of excess mobility[1] driven by worker-sector mismatch, the literature has devoted little attention to its impact on the wage-tenure relationship. This paper bridges that gap.

Developing a stochastic dynamic model of wages and mobility represents the primary contribution of this paper. The key addition in the model is the presence of dynamic worker-sector mismatch. This allows one to quantify each of the aforementioned three forces: sector-specific skill accumulation, sectoral-shocks, and worker-sector mismatch. We show that mismatch plays an essential role in capturing the wage-tenure relationship and mobility decision. Furthermore, the model allows for a characterization of the bias in estimates

[1] As in Davis and Haltiwanger (1992), net mobility refers to the gap between the simultaneous in- and outflows at the sectoral level, while excess mobility is overall (or gross) mobility minus the net mobility. In other words, excess mobility refers to in- and outflows that cancel at the sectoral level. For recent studies on equilibrium multi-sector economies with excess worker mobility, see Coen-Pirani (2010) and Lkhagvasuren (2012).

of the skill-premium when mismatch is ignored. We find this bias to be non-trivial.

The model builds on McLaughlin and Bils (2001) who use Roy's (1951) seminal theory of sectoral selection and the wage distribution (also see Moscarini, 2001, and Heckman and Taber, 2008, for extensions of Roy's model).[2] In our model, within each sector, there exist high and low skilled workers. Skill is determined by sector-specific skill accumulation; that is, workers may receive a skill premium. The longer a worker stays in a sector, the more likely it becomes they receive the skill premium. Workers are further subject to two shocks. One shock is a persistent idiosyncratic productivity shock. This shock affects the relative productivity of the *individual* in one sector relative to the other. We refer to such shocks as "worker-sector mismatch" or "mismatch" shocks. For certain values of the shock, workers may decide to change sectors, facing a moving cost when doing so.

This dynamic worker-mismatch component represents the key innovation of our model, relative to the existing static Roy-frameworks in McLaughlin and Bils (2001) and Heckman and Taber (2008). As in Rogerson (2005) and Kambourov and Manovskii (2008), there also exists a persistent sector-level shock affecting all workers within a particular sector. The sectoral shock causes net mobility, while the dynamic mismatch shock creates excess mobility. To quantitatively evaluate the model, we first describe the key relationships between wages and mobility in PSID data. There exist several key facts.

First, movers have lower wages (on average) in both the origin and destination sectors (also see McLaughlin and Bils (2001)). For movers, while indeed wages increase with tenure, the wage-tenure profile remains relatively flat. The

[2]Following the tradition of the literature on sectoral selection and wages, the current paper builds on Roy's (1951) model and introduces human capital accumulation and a dynamic sector match shock to the model. Others have introduced these elements mainly to the Lucas and Prescott (1974) island model. For example, Rogerson (2005) and Kambourov and Manovskii (2008) extend the island model by considering sector specific human capital accumulation and analyze the impact of mobility on employment and wages. Coen-Pirani (2010) shows that an idiosyncratic preference shock specific to the worker-location match can explain salient features of labor flows across US states. Lkhagvasuren (2012) argues that an idiosyncratic location match shock to worker productivity might be essential for the procyclical gross mobility and local unemployment differences.

average wage among movers is below that of stayers in the destination sector, and this initial wage "loss" takes more than seven years to recover. Similar patterns in the PSID are also noted by Kambourov and Manovskii (2008) and Moscarini and Thomsson (2007) under different definitions of a sector.

These patterns are typically taken as evidence of a sector-specific skill premium. Workers experience a drop in wages (relative to those currently in the destination sector) because they lack the skill premium possessed by those already in the sector. Wages subsequently increasing with tenure provides further evidence of sector-specific human capital accumulation.

We estimate the wage-tenure relationship controlling for several characteristics including age and education and the pattern still exists. Of course, as Topel (1991) notes, this observed wage-tenure relationship may simply be the result of mobility being correlated with other unobserved individual characteristics, including productivity. By including the dynamic worker-mismatch component, the analysis in this paper allows us to control for these unobservable.

Our data analysis also produces a novel fact: there exists a negative correlation between sectoral mobility and lifetime earnings. This correlation further highlights the difficulties in understanding the forces driving the wage-mobility relationship. That is, the wage-tenure relationship described above may be the result of opportunistic moves resulting from worker-sector mismatch. Or, it may be further evidence that the propensity to move is innately related to the same characteristics driving differences in skill. Our dynamic model with excess mobility captures this fact, and the analysis explores which factors (skill-premium, sectoral-shocks, or worker mismatch) drive the relationship.

Using the estimates of the wage-tenure relationship and the lifetime earnings mobility relationship, the model is calibrated and quantitatively evaluated. It does well capturing the wage-tenure relationship, where we focus on the first $5-6$ years following mobility. The model also matches the negative correlation between lifetime earnings and mobility.

Highlighting the advantages of the dynamic model we then explore which forces drive which features of the data. As in Topel (1991), among others, we find that sector-specific skill accumulation plays an important role in explaining the wage-tenure relationship. We find, however, that the persistent worker-sector mismatch shock also plays an important role. The analysis also characterizes the bias in the returns to sector-specific skill accumulation that would occur if one ignored the mismatch dimension and attributed all wage growth to skill accumulation. Around 20 percent of wage growth is the result of mismatch-driven mobility. That is, a model without the dynamic worker-sector mismatch component *overestimates* the skill premium by 20 percent.

These findings have an important implication on the value of a job. According to Topel (1991), 10 years of job tenure raises the wage by 25 percent and this represents what a typical worker would lose if the job were to end exogenously. We find that because of the match shock, the value of a job is substantially higher than those measured by the wage-tenure profile.

Moreover, the results indicate that the sectoral-shocks (i.e., net mobility) have little impact on the results. To determine the relative impact of these two shocks, the model is simulated with no sector-specific shocks. This implies the relative employment across sectors is constant. In this case, however, the wage-tenure relationship is unchanged from the baseline case. This implies that the dynamic mismatch shocks, and thus excess mobility, are the key unobservable shocks driving the results in our model.

Finally, to further emphasize the value added by the dynamic worker-sector mismatch component, the model is re-calibrated with no skill premium and no moving costs. When the mismatch shock has sufficient persistence, the model still captures the key features of the wage-tenure relationship and the negative correlation of mobility and lifetime earnings. Intuitively, relatively high persistence in the mismatch shock implies that those workers who find a suitable match for their particular skills are more likely to experience further improvements in the productivity of the match. While the baseline calibration implies an important role for the skill premium, a model featuring only the dynamic worker-sector mismatch component is still capable of capturing salient features of the data on wages and mobility.

The remainder of the paper is organized as follows. Section 2 details the facts characterizing the wage-mobility relationship. Section 3 describes the model. Section 4 describes the calibration and the main results. In Section 5 we perform counterfactual experiments to disentangle the effects driving the key features of wage-mobility relationship. Section 6 analyzes the role of match shock and Section 7 concludes.

2 Patterns of Wage and Mobility

This section summarizes the key patterns of sectoral mobility and wages. The analysis uses data from the Panel Study of Income Dynamics (PSID), and further restricts attention to the Retrospective Occupation-Industry Supplemental Data Files, released in 1999. Kambourov and Manovskii (2009a) find that the Retrospective Files for the period of 1968-1980 provide a more accurate measure of labor mobility across industries and occupations than the main PSID data. A more accurate mobility variable is important for our purpose as we focus on the individual-level relationship between mobility and wages. For example, when we include less accurate measure of mobility in the main PSID data of 1981-1997, the relationship between mobility and earnings becomes weaker (see Table A.4) while the main data patterns discussed in this section remain robust.[3]

The sample consists of 3057 male household heads aged 20-65, totalling 28443 years of observations over the period 1968-1980. In the analysis, "sectors" are defined as industries. Towards this end, consider four broad industries: Agriculture, Manufacturing and mining (hereafter Manufacturing), Services, and Public Sector.[4] Sectoral mobility occurs if an individual switches

[3]At this point, it should be re-emphasized that we focus on the individual-level relationship between mobility and wages. Others have analyzed more aggregate features of sectoral dynamics that happened in the recent past; see, for example, Lee and Wolpin (2006), Kambourov and Manovskii (2009a), Jaimovich and Siu (2012) and Autor and Dorn (2013).

[4]McLaughlin and Bils (2001) argue that to measure the wage gap between inter-sectoral movers and stayers, one needs large sectors, as movers are a small fraction of the labor force. On the other hand, the PSID surveys a few thousand individuals and thus the total number of movers for a given year is small in the dataset. For these considerations, to construct a reliable wage-tenure profile, we focus on the above broad sectors. Lee and Wolpin (2006) also focus on mobility between Manufacturing and Service sectors. Section 5.2 discusses

industries between two consecutive years in which he is employed. Wages are measured as real hourly wages, computed as annual labor income divided by annual hours and deflated by the *Consumer Price Index for All Urban Consumers* provided by Bureau of Labor Statistics (BLS).

There exist several key patterns in the data linking sectoral-mobility and wages. We begin by detailing how wages differ before and after a sector switch. The relationship between lifetime earnings and mobility is then characterized.

2.1 Net and excess mobility

According to the sample, from 1968 and 1980, 6.78 percent of the workers change sectors each year. This number is computed using 25310 year-and-person records for which mobility can be assessed; i.e., observations for which there is a known previous industry. Table 1 decomposes this excess mobility by type of moves. Specifically, the table divides the sample into sixteen different cells by the previous and current sector of workers. The bottom entry of each cell of the sixteen cells displays the total number of individuals moving across sectors. The table shows that most mobility occurs between Manufacturing and Service sectors. Over the sample period more than 500 workers move from the Service sector to Manufacturing sector. The Service sector receives roughly the same number of workers from Manufacturing with the corresponding net flow of only seven workers.

Although the sample size and the small percentage of workers that move across sectors considerably affects the precision of the net flow, these numbers suggest that net mobility constitutes a small share of excess mobility. Below in Section 4.1.1 we measure net mobility more precisely using the volatility of sectoral employment and show that net mobility is indeed very small relative to excess mobility. Both of these features serve as the main motivation for focusing on excess mobility. As in Jovanovic and Moffitt (1990), this excess mobility is driven by a sector-specific match shock.

how our results are related to an alternative or narrower definition of the sector.

2.2 Wage levels of movers

Next we examine how mobility and wages are related in the PSID. We measure real hourly wages relative to those who do not switch sectors (i.e., the wages of stayers is normalized to 1). The first two entries of each of the sixteen cells in Table A.1 report the mean real hourly wages of workers in their previous and current sector. For example, consider workers moving from Service to Manufacturing between time $t-1$ and t. Their wage before changing industries is 74 percent of the average wage among workers who remain in the Service sector. Once these movers arrive at Manufacturing, on average their wage is 70 percent of those who started and stayed in Manufacturing.

The first two entries of the off-diagonal cells in Table 1 summarize two important features of wages for movers. First, movers have lower wages (on average) in the origin sector, relative to non-movers (stayers). Second, upon moving, they have lower wages (on average) in the destination sector. The exception is workers moving from Manufacturing and Agriculture, where individuals experience an increase in wages after moving. McLaughlin and Bils (2001) also analyze these features but focusing mainly on net mobility.

As shown in Table 1, movers have lower wages (on average) in both the origin and destination industries. Of course, this could exist simply because younger or less educated workers move more often across sectors (see Table A.1 in Appendix A). For this reason, next we measure the wage-tenure profile for movers controlling for age and education. This wage-tenure profile is central to our dynamic analysis of wages and mobility below.

2.3 Evolution of wages of movers

First we compute the individual's quantile in the empirical distribution of the hourly wage within each cell along age, education, year and sector. The quantiles are smoothed using a local regression (local polynomials of degree 0) of quantile on years since mobility. More precisely, the mean quantile τ years after mobility is computed on those for whom we observe at least τ years of employment in the same sector after moving. Sector tenure 0 is assigned to

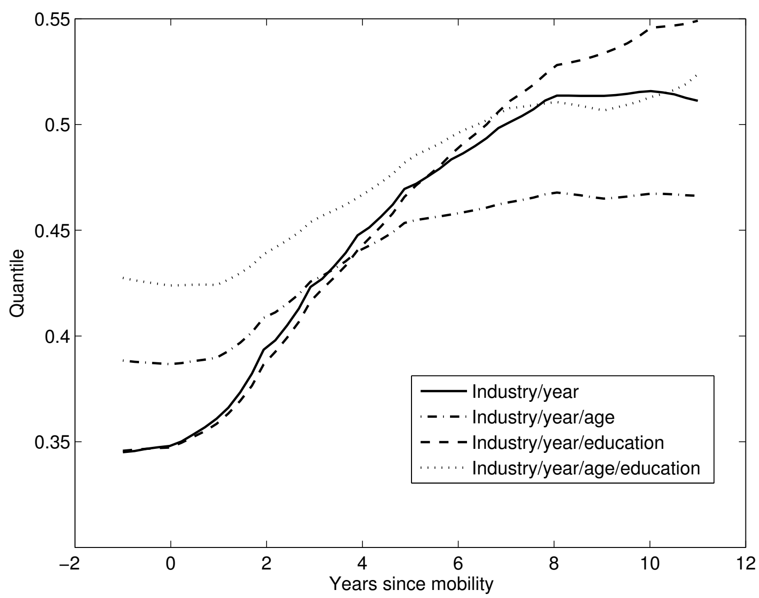
Table 1: Patterns of Sectoral Mobility and Wages

Previous sector, j	*Variables*	*Current sector, j'* agricult.	manufact.	service	public	all, N_j
agricult.	w_{-1}	1	0.92	0.84	0.81	
	w_1	1	0.43	0.59	0.44	
	$N_{j,j'}$	1,101	86	74	7	1,268
	$\frac{N_{j,j'}}{N_j} \times 100\%$	86.8%	6.8%	5.8%	0.6%	
manufact.	w_{-1}	0.59	1	0.75	0.75	
	w_1	1.11	1	0.74	0.64	
	N_{obs}	70	10,371	541	63	11,045
	$\frac{N_{j,j'}}{N_j} \times 100\%$	0.6%	93.9%	4.9%	0.6%	
service	w_{-1}	0.61	0.74	1	0.74	
	w_1	0.94	0.70	1	0.69	
	N_{obs}	71	534	10,328	103	11,036
	$\frac{N_{j,j'}}{N_j} \times 100\%$	0.6%	4.8%	93.6%	0.9%	
public	w_{-1}	0.53	0.56	0.80	1	
	w_1	0.96	0.59	0.77	1	
	N_{obs}	5	57	104	1,795	1,961
	$\frac{N_{j,j'}}{N_j} \times 100\%$	0.3%	2.9%	5.3%	91.5%	

Notes: There are sixteen cells associated with each pair of the previous (origin) and current (destination) industries. A row corresponding to w_{-1} is the mean wage of those who will move in the next period relative to the mean wage of those who will stay in the next period. A row corresponding to w_1 is the mean wage of those who arrived at their destination sector within the last year relative to the mean wage of the incumbent workers of the sector. The wage is measured by hourly rate. N_j stands for the number of workers by their previous sector j, while $N_{j,j'}$ is the number of workers switching from sector j to sector j'.

those with tenure less than one year. The wages for sector tenure -1 refer to the wage in a movers' previous sector. The sample size decreases moving to the right along the horizontal axis. The smoothed quantiles obtained under different specifications are plotted in Figure 1.

Figure 1: Wages by Sectoral Tenure



Notes: The figure plots the wage of recent movers as a function of sectoral tenure. Wages are measured in quantiles. Specifically, the profile labeled "Industry/year" plots the wages of the average worker. The other profiles plot the same variable, but control for age and education. Each profile is smoothed using local polynomials.

The figure confirms that a worker's wage are below their group median prior to, and after the move. Wages increase with tenure in their new sector, but remain below the median of the otherwise observationally identical workers of the new sector for seven or more years after mobility.

2.4 Mobility and life-time earnings

The link between sectoral mobility (computed from the 1968-1980 Retrospective Files) and life-time earnings (computed from the full sample, 1968-2007) is now examined. Identifying this relationship plays an important role in the quantitative analysis in Section 4. Specifically, the correlation between lifetime earnings and mobility is closely related to the magnitude of the sector-specific skill premium.

The logical outcome of our results above is the following. Mobility is associated with lower wages both before and after a move. Given this, one may ask whether lower wages are caused by a transitory productivity shock, or if they stem from a more permanent productivity difference (e.g., mobility differences between skilled versus unskilled workers). In the latter case, one may expect to see a negative relationship between life-time earnings and mobility. Indeed, individuals with lower life-time earnings are more mobile.

To measure an individual's propensity to move, several mobility indexes are constructed. First, consider the individual-specific mean of the mobility dummy (over the period covered by the Retrospective Files), which represents the most parsimonious index. Denoting this index by $\mathcal{M}_i^{\mathrm{a}}$, we define it as: $\mathcal{M}_i^{\mathrm{a}} = \frac{1}{T_i-1}\sum_{t=1}^{T_i-1} m_{it}$, where T_i is the number of years of observations for individual i and m_{it} is a dummy variable for changing industries between the periods $t-1$ and t.

To control for the fact that mobility varies with age and education (see Table A.1), consider the following normalized index: $\mathcal{M}_i^{\mathrm{b}} = \frac{1}{T_i-1}\sum_{t=1}^{T_i-1} m_{it}/\tilde{m}_{it}$, where $\tilde{m}_{it}$ is the average mobility rate among individuals in the same age and education group as person i at time t. To ensure the robustness of these measures, we also compute quantile versions of these two indexes. Let $\mathcal{M}_i^{\mathrm{c}}$ and $\mathcal{M}_i^{\mathrm{d}}$ denote the quantile versions of $\mathcal{M}_i^{\mathrm{a}}$ and $\mathcal{M}_i^{\mathrm{b}}$, respectively.[5]

Similarly, life-time earnings is measured with several indexes. $\mathcal{E}_i^{\mathrm{a}}$ is the

[5] Because of the finite number of age and education cells and the low mobility rate, more than one person can share a particular value of the level index $\mathcal{M}_i^{\mathrm{a}}$ or $\mathcal{M}_i^{\mathrm{b}}$. For example, there are 37 unique values of $\mathcal{M}^a$. To avoid any possible bias caused by this discrete nature of the indexes, we construct the quantile indexes by imposing the same quantile on those who are tied along the associated level index.

Table 2: Individual-Level Mobility and Life-Time Earnings

	Life-time earnings				
Individual-level mobility	$\mathcal{E}^{\mathrm{a}}$	$\mathcal{E}^{\mathrm{b}}$	$\mathcal{E}^{\mathrm{c}}$	$\mathcal{E}^{\mathrm{d}}$	$\mathcal{E}^{\mathrm{e}}$
$\mathcal{M}^{\mathrm{a}}$	-0.200	-0.205	-0.141	-0.124	-0.138
$\mathcal{M}^{\mathrm{b}}$	-0.157	-0.161	-0.152	-0.145	-0.156
$\mathcal{M}^{\mathrm{c}}$	-0.220	-0.226	-0.168	-0.155	-0.171
$\mathcal{M}^{\mathrm{d}}$	-0.189	-0.197	-0.172	-0.169	-0.179

Notes: *Individual-level mobility* ($\mathcal{M}$) refers to the number of moves a worker made during the sample period. *Life-time earnings* ($\mathcal{E}$) measures the average of the residual log hourly wages of a particular worker over the sample period. The table displays pairwise correlations of various measures of the two variables across individuals. The p-values associated with these correlations are all less than 0.01.

individual fixed effect estimated from a fixed-effect regression of log hourly wage on total sector experience, and full sets of dummies (age, year, state, education, and sector). $\mathcal{E}_i^{\mathrm{b}}$ is the quantile of $\mathcal{E}_i^{\mathrm{a}}$. $\mathcal{E}_i^{\mathrm{c}}$ is the individual-specific mean residual from an OLS regression that is similar to the fixed-effects case (also see Moffitt and Gottschalk, 2002). $\mathcal{E}_i^{\mathrm{d}}$ is the individual-specific mean quantile of OLS residuals, and finally $\mathcal{E}_i^{\mathrm{e}}$ is the quantile of individual-specific mean OLS residuals.

Table 2 displays the correlations for each pair of measures. All the correlations are negatively significant, indicating that individuals with lower life-time earnings are more mobile.

On the surface, the aforementioned relationships between wages and mobility appear in contradiction to the theory that workers move to pursue better employment opportunities and wages. What a workers wage *would have been* had they decided to stay in the original sector is unobservable, however. This represents the key difficulty in drawing such conclusions from the data. To disentangle the potential forces driving the patterns established in this section, the next section presents a dynamic model with joint determination of wages and mobility.

3 Model

To uncover the forces underlying the relationship between wages and sectoral mobility, the model builds on McLaughlin and Bils (2001) who use Roy's (1951) framework to study the wages of sector movers relative to that of incumbent workers. Specifically, we consider a dynamic Roy model with the following features.

Workers acquire sector specific skills (e.g., Rogerson (2005) and Kambourov and Manovskii (2009a)), and are subject to an idiosyncratic productivity shock specific to the worker-sector match. The idiosyncratic shock is referred to as the "worker-sector mismatch shock" or "mismatch shock." There also exists a sectoral shock that affects all workers within a particular sector. Workers face explicit moving costs when switching sectors. In the model, the sectoral shock causes net mobility, while the worker-sector mismatch shock creates excess mobility. So, in contrast to the standard Roy model, which allows for only net mobility, our model permits both net and excess mobility.

3.1 Environment

There exists two sectors denoted by 0 and 1. Each sector is inhabited by a large number of workers. A worker's wage in a particular sector is determined by three components: sector-specific skill accumulation, a sectoral shock, and the worker-sector mismatch shock.

For sector-specific human capital, we adopt the specification of Kambourov and Manovskii (2009a). Individuals are either skilled or unskilled in their current sector, and a worker can only be skilled in one sector at a time.[6] A skilled worker is more productive than an otherwise identical unskilled worker (in the same sector). In each period, an unskilled worker becomes skilled in the current sector with probability p. Let $\pi > 0$ denote the skill premium that

[6] See Lazear (2009) and Gathmann and Schonberg (2009) for alternative views of human capital where there is transferability of skills across sectors. Also, similarly to Kambourov and Manovskii (2009a), we do not allow workers to exert effort to increase their specific skills. In the presence of such effort, the persistence of the two income shocks (x and z) could substantially raise the correlation between life-time earnings and mobility.

this worker receives. Notice, the longer an agent remains in the current sector, the more likely they are to be skilled; therefore, tenure is required to become skilled. Moreover, each period a worker exits labor market with probability δ, while newly born workers enter the economy.

There also exists a sectoral shock. It affects the productivity of all workers in one sector relative to the other sector. Specifically, all workers in sector 1 are subject to the shock z_t. This shock has a stationary transition function $\Pr(z_{t+1} < z'|z_t = z) = G(z'|z)$ given by the following autoregressive process:

$$z_{t+1} = \rho_z z_t + u_t, \tag{1}$$

where $\rho_z \geq 0$ and u_t is a zero-mean random variable. Let σ_z denote the unconditional standard deviation of z_t: $\sigma_z = \mathrm{Std}(z_t)$.

Finally, an individual receives a dynamic mismatch shock denoted by x. This shock evolves according to the following AR(1) process

$$x_{t+1} = 1 - \rho_x + \rho_x x_t + \epsilon_t \tag{2}$$

where $\rho_x \geq 0$ and ϵ_t is also a zero-mean normal random variable. Let $\mathrm{Std}(x_t) = \sigma_x$. Let F denote the transition function for x_t: $\Pr(x_{t+1} < x'|x_t = x) = F(x'|x)$.[7]

3.2 Wages

The current wage for workers in sector 0 is given by,

$$w_0(h, x, z) = \pi h + x \tag{3}$$

[7]We present the model in terms of two sectors, 0 and 1. The model, however, can be recast as an economy with N sectors by interpreting x as the worker's mismatch shock in the current sector (i.e., sector 1), and $-x$ as the highest of the $N-1$ mismatch shocks from the remaining $N-1$ sectors.

and for workers in sector 1,

$$w_1(h, x, z) = \pi h - x + z, \tag{4}$$

where h is a dummy whether a person is skilled in their current sector. Equations (3) and (4) imply that individual productivity is *perfectly-negatively* correlated across sectors; the best-matched workers in sector j are the worst-matched workers of sector $1 - j$.[8] Equations (3) and (4) display the role played by the mismatch shock. For example, suppose a worker currently employed in sector 1 receives a shock $x > 0$. This shock makes the worker more productive in sector 0 relative to sector 1. For large enough x, the worker may prefer to switch sectors. Moving is costly, however, as we specify below.

3.3 Timing

Each period consists of four stages. In the first stage, individuals observe the sectoral shock, z, and the mismatch shock x. In the second stage, after observing these shocks, individuals decide which sector to work in. Workers moving between sectors start as unskilled in the new sector. In the third stage, individuals supply one unit of labor and receive the wage. That is, production or work occurs during the third stage. In the fourth stage, some of the unskilled workers become skilled. Simultaneously, some workers leave the labor market and new (i.e., unskilled) workers enter the market. Let $b_{j,t}$ denote the number of new entrants to sector j at t.

[8] Rogerson (2005) and Moscarini and Vella (2008) consider similar, *perfectly-negatively* correlated individual productivity across sectors. However, unlike in their models, sector-specific productivity is stochastic in the current model. One can consider labor income shocks that are not perfectly correlated across sectors. For example, suppose $\tilde{x}_{0,t}$ and $\tilde{x}_{1,t}$ denote these shocks and follow the same autoregressive process $\tilde{x}_{0,t} = \rho \tilde{x}_{0,t-1} + \epsilon_{0,t}$ and $\tilde{x}_{1,t} = \rho \tilde{x}_{1,t-1} + \epsilon_{1,t}$ where the innovations $\epsilon_{0,t}$ and $\epsilon_{1,t}$ are such that $\mathrm{Corr}(\epsilon_0, \epsilon_1) < 1$. However, given that the paper focuses on the wage of movers relative to that of stayers, one can obtain the same result by using the following decomposition: $\epsilon_{0,t} = v_{A,t} + v_{B,t}$ and $\epsilon_{1,t} = v_{A,t} - v_{B,t}$, where $v_{A,t}$ and $v_{B,t}$ are uncorrelated shocks.

3.4 Relationship between mobility and wages

Before continuing the formal analysis of the model, it is useful to briefly discuss how mobility and wages are interrelated in this dynamic extension of Roy's (1951) model.

First, consider a simple case with no moving costs, no skill premium, and no net mobility; i.e., $c = 0$, $\pi = 0$, and $z = 0$. If the mismatch shock is purely transitory ($\rho_x = 0$), there is no wage gap between movers and stayers. If the labor income shock becomes persistent ($\rho_x > 0$), however, incumbent workers draw their match shock from a better (conditional) distribution than movers. Consequently, the incumbents of each sector have a higher wage than new arrivals, on average. Indeed, the quantitative analysis below shows that this effect accounts for a considerable portion of wage growth among recent movers.

Now suppose that a worker incurs a direct moving cost $c > 0$. A higher moving cost implies lower mobility for a given dispersion of the mismatch shock (i.e., for a given level of σ_x). Thus, one can generate the same level of mobility using different combinations of σ_x and c. In other words, one can obtain the same level of mobility using a lower dispersion of the mismatch shock and a lower moving cost, or by using a higher dispersion of the mismatch shock and a higher moving cost. These alternative scenarios, however, have very different quantitative implications for the wages of movers. Specifically, the wage of movers is higher in the latter case (i.e., high σ_x and c) since the moving cost amplifies the selection effect along the mismatch shocks.

Finally, re-introducing sector-specific skill accumulation causes the wage gap between movers and stayers to become larger. Since skilled workers move less than unskilled workers, there exists a substantial wage gap between movers and stayers. Also, mobility declines with the skill premium. Therefore, measuring the skill premium requires knowing both the level of mobility and the wage gap between movers and stayers. These considerations are important in the quantitative analysis in Section 4.

3.5 Value functions

Let $U_j(h, x, z)$ denote the life-time utility of a worker with skill level $h \in \{0, 1\}$ in sector $j \in \{0, 1\}$, where x and z represent the mismatch and sector shocks, respectively. This represents the utility associated with the moment following the realization of the shocks, but preceding the mobility decision stage.

3.5.1 Skilled stayers

For a skilled worker in sector j, the life-time utility of staying in j is given by

$$S_j(1, x, z) = w_j(1, x, z) + \beta(1 - \delta) \iint U_j(1, x', z') dF(x'|x) dG(z'|z), \tag{5}$$

where β is the time-discount factor.

3.5.2 Unskilled stayers

For an unskilled worker in sector j, the life-time utility of staying in j is given by

$$\begin{aligned} S_j(0, x, z) = \quad & w_j(0, x, z) + \beta(1 - \delta) \left\{ p \iint U_j(1, x', z') dF(x'|x) dG(z'|z) \right. \\ & \left. +(1 - p) \iint U_j(0, x', z') dF(x'|x) dG(z'|z) \right\}. \end{aligned} \tag{6}$$

3.5.3 Movers

Life-time utility for a worker moving from sector j to $1 - j$ is given by

$$M_j(x, z) = S_{1-j}(0, x, z) - c, \tag{7}$$

where c denotes the moving cost.

3.5.4 Mobility decision

Given the value functions S_j and M_j, the life-time utility of a worker with skill level (h, x, z) is given by

$$U_j(h, x, z) = \max\{S_j(h, x, z), M_j(x, z)\}. \tag{8}$$

Let Ω_j denote the decision rule governing whether a person in sector j stays in her current sector:

$$\Omega_j(h, x, z) = \begin{cases} 1 & \text{if } S_j(h, x, z) \geq M_j(x, z), \\ 0 & \text{otherwise.} \end{cases} \tag{9}$$

3.6 Measures and sectoral dynamics

Let $\tau \in \{0, 1, 2, \cdots\}$ denote the number of periods a person has worked in their current sector for (since entering the labor market or since moving). At any t, a worker in sector j is fully characterized by her skill level h, mismatch shock x, and sector tenure τ. Let $\mu_{j,t}(h, x, \tau)$ denote the number of workers in state (h, x, τ) in sector j at the end of period t. The next period's measure $\mu_{j,t+1}(h, x, \tau)$, $j \in \{0, 1\}$, is determined by the current measures $(\mu_{0,t}(h, x, \tau), \mu_{1,t}(h, x, \tau))$ and the next period's sectoral shock z_{t+1}. Let Γ_{t+1} denote this evolution.

Normalize the total number of workers in the economy to 1:

$$\sum_h \sum_\tau \int (\mu_{0,t}(h, x, \tau) + \mu_{1,t}(h, x, \tau))dx = 1 \tag{10}$$

for each $t \in \{0, 1, 2, \cdots\}$. Furthermore, let $\nu_{j,t}(h, x)$ denote the measure of workers after the realization of the mismatch shocks in period t:

$$\nu_{j,t}(h, x, \tau) = \int \mu_{j,t-1}(h, \tilde{x}, \tau) \frac{\partial F(x|\tilde{x})}{\partial \tilde{x}} d\tilde{x}. \tag{11}$$

Then, the total number of workers moving from j to $1 - j$ for each x at time t is given by

$$m_{1-j,t}(x) = (1-\delta)\sum_h \sum_\tau (1-\Omega_j(h,x,z_t))\nu_{j,t}(h,x,\tau), \tag{12}$$

where z_t is the sectoral shock at time t. At the end of the current period, these movers will have worked for one period at their destination:

$$\mu_{j,t}(0,x,1) = m_{j,t}(x). \tag{13}$$

For stayers, sectoral dynamics is captured by the following two equations: for unskilled workers,

$$\mu_{j,t}(0,x,\tau+1) = (1-\delta)(1-p)\Omega_j(0,x,z_t)\nu_{j,t}(0,x,\tau), \tag{14}$$

and for skilled workers,

$$\mu_{j,t}(1,x,\tau+1) = (1-\delta)\left(\Omega_j(1,x,z_t)\nu_{j,t}(1,x,\tau) + p\Omega_j(0,x,z_t)\nu_{j,t}(0,x,\tau)\right), \tag{15}$$

where $\tau \in \{1,2,\cdots\}$. Finally, the number of new workers born in sector j is proportional to the sector's unskilled employment,

$$b_{j,t} = \frac{\delta \sum_{\tau\geq 1} \int \mu_{j,t}(0,x,\tau)dx}{\sum_{\tau\geq 1} \int (\mu_{0,t}(0,x,\tau) + \mu_{1,t}(0,x,\tau))dx} \tag{16}$$

and their initial match shock is zero:

$$\mu_{j,t}(0,x,0) = b_{j,t} I(x), \tag{17}$$

where $I(x)$ is an indicator function equal to 1 if $x = 0$, and equal to 0 otherwise.

3.7 Definition of the Equilibrium

The equilibrium consists of a set of value functions $\{U_j,\ S_j,\ M_j\}$, a decision rule Ω_j, a sequence of the sectoral technology shock $\{z_t\}_{t=1}^{T}$ for an integer $T > 0$, and the sequence of measures $\{\mu_{j,t}(0, x, \tau),\ \mu_{j,t}(1, x, \tau)\}_{t=0}^{T}$ for any j, τ and x such that

1. stayer: given U_i, the value function $S_j(h, x, z)$ solves equations (5) and (6);
2. mover: given S_j and M_j for each j, the decision rule $\Omega_i(x)$ and the value function $U_i(x)$ solve equation (8); and
3. consistency of the law of motion: for each triplet (x, j, τ), $\{\mu_{j,t}(0, x, \tau),\ \mu_{j,t}(1, x, \tau)\}_{t=1}^{T}$ satisfy equations (10) through (16), subject to the sequence of the sectoral technology shock $\{z_t\}_{t=1}^{T}$ and the initial measure $\{\mu_{0,0}(h, x, \tau),\ \mu_{1,0}(h, x, \tau)\}$.

3.8 Computation

Accounting for both the mismatch and sectoral shocks in the presence of sector-specific skill accumulation implies a computationally intensive task. Moreover, one must keep track of wages for each person by their sectoral tenure. Thus, both the solution and simulation amounts to a stochastic dynamic problem with a large state space.

To solve the model, we discretize the state space along x and z. The sectoral technology shock, z, is approximated by a three-state Markov chain. A relatively fine grid for x is necessary to generate the observed level of mobility and the wage gap between movers and stayers. For this reason, the stochastic process for x is approximated by a 51-state Markov chain. The Markov chains are constructed using the finite-state process of Rouwenhorst (1995).[9] Then, using value function iteration, we find the decision rule in equation (9) for each sector j and for each discrete value of x, z and h.

Next we draw the sequence of the three-state z shock for $T = 2000$ periods while keeping track of the distribution of heterogeneous agents over (j, h, x, τ).

[9] Galindev and Lkhagvasuren (2010) show that the method of Rouwenhorst (1995) outperforms the other commonly used discretization methods for highly persistent AR(1) shocks.

For the initial measures, $\mu_{j,0}(h,x,\tau)$, $j \in \{0,1\}$, we consider the case that all workers are unskilled (i.e., $h = 0$) and distributed equally between the two sectors. Their within-sector distribution over the mismatch shock x is given by a normal distribution with mean 0 and variance σ_x^2, and their sector tenure is 1 (i.e., $\tau = 1$).

Before we calculate the moments in the simulated data, we discard the first 500 periods. Increasing T does not have significant impact on the moments. To measure life-cycle income and individual-level mobility, we consider the wages and mobility for 50,000 individuals. The other moments are measured more precisely using the measure of 1 individual over the discrete states.

4 Quantitative Analysis

The model in Section 3 provides a flexible framework to analyze the relationship between wages and mobility in the presence of both net and excess mobility. This section examines, quantitatively, how well the model captures the key relationships characterized in Section 2. First the model is calibrated to evaluate how well it matches several un-targeted moments in the data. Then, several counterfactual experiments are performed to illuminate which mechanisms appear to drive the observed wage-mobility relationships.

4.1 Calibration details

Several of the model parameters can be set directly from the data. The remaining parameters are calibrated so that the equilibrium predictions of the model are consistent with certain moments in the data.

The time period is one year. We set $\beta = 1/1.04$, consistent with an annual interest rate of 4 percent. The probability of leaving the labor market (or retiring), δ, is set to 0.025, implying an expected working lifetime of 40 years. The probability of becoming skilled, p, is set following Kambourov and Manovskii (2009a). Specifically, we observe that the positive slope of the wage-tenure profile decreases sharply at the tenure levels of 11 to 13 years. Accordingly, we set $p = 1/12$, implying an average duration of 12 years to become skilled in a particular sector. Below in Figure 2, we analyze the robustness of the model predictions to different values of p.

This leaves the parameters governing the sector specific shock z_t (ρ_z and σ_z), the mismatch shock x (ρ_x and σ_x), the skill premium π, and moving costs c to be determined. We describe the calibration of each below.

4.1.1 Sector-specific shock

From equation (1), the process for the sector-specific productivity shock, z, requires values for the parameters ρ_z and σ_z. To measure z_t, we use annual per-worker output from 1987 through 2012, tabulated by the Bureau of Labor Statistics (BLS). Similarly to Blanchard and Katz (1992), we measure z_t as the difference between average output in the Manufacturing sector relative to the entire U.S. economy (measured in log-differences). For the U.S. economy, we use the Non-Farm Business Sector. We take the standard deviation and annual autocorrelation of this relative productivity from the trend (HP filtered with smoothing parameter 100). This implies $\sigma_z = 0.0068$ and $\rho_z = 0.4236$. The results are not sensitive to the particular time period used here (1987-2012), which we discuss in more detail in Appendix B.1.

4.1.2 Worker-sector mismatch shock

To calibrate the persistence of the mismatch shock x, ρ_x, the annual mobility rate of 6.78 percent (see Section 2) is targeted. Intuitively, a more persistent x shock implies low excess mobility, less persistence implies high excess mobility. Large mismatch shocks induce mobility, and when these remain persistent, overall mobility is low (similar effects are described by Bayer and Juessen (2012)). The 6.8 percent mobility rate implies $\rho_x = 0.4593$.

The dispersion of the mismatch shock is calibrated using the volatility of sectoral employment. The reason is as follows. If σ_x is low relative to σ_z, sectoral employment is more responsive to the z_t shock (and thus more volatile). Conversely, if σ_x is large relative to σ_z, labor mobility is less sensitive to z_t, and employment is less volatile.

Similarly to the case of sectoral output above, we measure sectoral employment using the Manufacturing sector relative to aggregate (non-farm business) employment. Specifically we take the log of Manufacturing employment minus the log of aggregate employment. As with per-worker output above, both employment series are tabulated by the BLS. We use annual data from 1987 to 2012 to calculate an unconditional standard deviation of Manufacturing employment (from its HP trend with the smoothing parameter 100) of 0.59 percent. This implies $\sigma_x = 0.1229$.

4.1.3 Skill premium and moving cost

The moving cost is estimated by targeting repeat mobility. Repeat mobility is defined as the probability that a worker moves, conditional on having moved in the previous period. From the PSID data repeat mobility is 27 percent; i.e., approximately one quarter of current movers move again in one period. For relatively low moving costs, there is less selection along the mismatch shock; i.e. the mobility decision is more sensitive to x. This increases the probability of receiving consecutive mobility-inducing shocks, implying high repeat mobility. High moving costs, however, imply workers must receive a relatively large mismatch shock to move. Since workers are less likely to receive two large shocks (in absolute terms) in consecutive periods, repeat mobility is low. Matching repeat mobility of 27 percent implies a moving cost $c = 0.0191$, or approximately 2 percent of the average annual wage.

The sector-specific skill premium, π, represents the final parameter to specify. To calibrate this parameter, we target the wage level of recent movers relative to the mean wage in the destination sector. Specifically, we target the mean log wage difference between workers who have worked in the current sector for one year since their last move and the average wage among all workers in the sector. Since the average worker in a sector is more skilled than the new comers, the skill premium has a direct impact on the wage of movers. The mean log wage gap between movers and stayers is -0.1803, requiring a skill premium of $\pi = 0.3288$. Table 3 displays the benchmark parametrization.

Table 3: Parameters

Parameters	*Values*	*Description*
β	0.9615	the time discount factor
δ	0.0250	the probability of retirement
p	0.0833	the probability of becoming experienced
ρ_z	0.4236	the persistence of the sector shock
σ_z	0.0068	the volatility of the sector shock
ρ_x	0.4593	the persistence of the mismatch shock
σ_x	0.1229	the dispersion of the mismatch shock
c	0.0191	the mobility cost
π	0.3288	the skill premium

Notes: The table summarizes the key parameters of the benchmark model.

4.2 Results

Table 4 presents the main results. First, the benchmark model performs well capturing the main patterns of mobility. Specifically, it matches the relative magnitude of excess and net mobility. Moreover, the model also matches observed repeat mobility. It is worth emphasizing that in a model with direct mobility, it is hard to generate the observed level of repeat mobility while focusing solely on net mobility.

The last three rows of Table 4 compare the model's predictions for three key un-targeted moments. First, the model does well capturing the wage growth of recent movers. The wage growth rate refers to annual wage growth of those who moved within the last five years. Specifically, we consider the log wage difference between those who arrived at a particular sector five years ago and those who arrived there one year ago, divided by four. We focus on the first five years after mobility for two reasons. First, in the PSID sample, there exist relatively few observations for workers with tenure greater than 5 years following mobility. Second and related, the average spell of employment in the sample is approximately 5 years; therefore, looking beyond 5 years likely brings unemployment spells into consideration, complicating the analysis (see Moscarini (2001), Rogerson (2005) and Lkhagvasuren (2012) for an analysis

Table 4: Benchmark Model

Moments	*Data*	*Model*
	Targeted moments	
mobility	0.0678	0.0677
volatility of sectoral employment	0.0059	0.0059
repeat mobility	0.2729	0.2633
movers' wage at destination	-0.1786	-0.1786
	Key predictions	
annual wage growth of recent movers	0.0259	0.0310
movers' wage at their origin	-0.1803	-0.2169
correlation of life-time earnings and mobility	-0.1523	-0.1822

of unemployment in related multi-sector models).

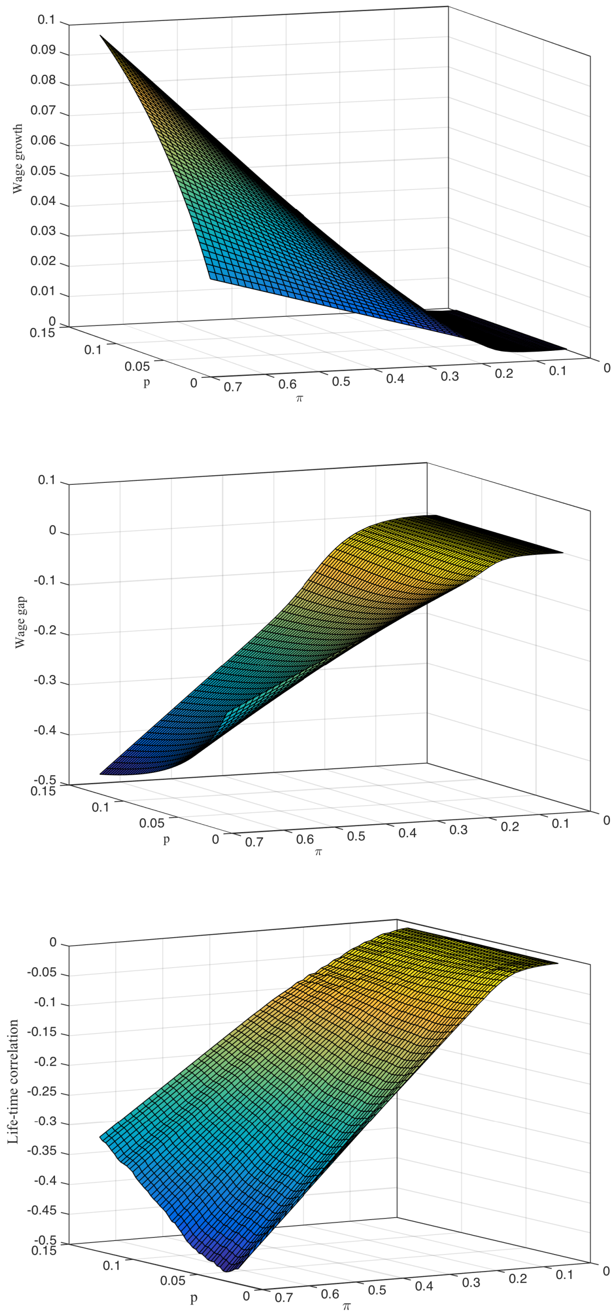
The model also captures the negative wage gap between movers and stayers at both the origin and destination. In Table 4, movers' wage at destination (origin) refers to the difference between the mean log wage of movers and that of the incumbent workers (the stayers).

The last row of Table 4 is of particular interest. Specifically, the model captures the negative correlation between lifetime income and mobility from Table 2. The value of the data moment corresponds to the correlation between the indexes $\mathcal{M}^b$ and $\mathcal{E}^c$ considered in Section 2. In the model, the correlation coefficient is constructed analogously, simulating income and mobility for 50,000 individuals.

Finally, in Figure 2, we analyze the robustness of these predictions to different values of p and π. Figure 2 shows the the moments respond gradually and monotonically to these parameters. More important, the figure shows that the moments do not always move together.

To further illuminate the role of the key elements of the model such as sector-specific skill accumulation and sectoral shocks, the analysis now considers several experiments.

Figure 2: Impact of Key Parameters



Notes: The figure plots the impact of the skill premium π and the probability of becoming skilled p on the key moments.

5 Numerical Experiments

This section uses the *benchmark model* to perform several counterfactual experiments disentangling the different effects driving the results presented above. The analysis begins by examining the role of the sector-specific skill premium, and then quantifies the relative impact of the two productivity shocks: sector-specific and mismatch.

5.1 Quantifying the impact of the skill premium

The skill premium, π, plays an important role in our analysis. To further understand its role in the wage-mobility relationship, we set $\pi = 0$ and simulate the model. Table 5 summarizes the results.

With no skill premium, mobility is large, increasing from 6.8 percent in the baseline case to 27.5 percent when $\pi = 0$. The skill premium works to reduce mobility substantially, consistent with Kambourov and Manovskii (2009a). The prospect of receiving the skill premium, or having already received it, makes workers less responsive to mismatch shocks. With no skill premium, workers move frequently in response to even relatively small mismatch shocks.

The results in Table 5 illuminate precisely the role of the skill premium in the model's ability to match the data (also see Figure 2). The skill premium appears to drive the model's ability to match the average wage of movers, before and after the move. In the baseline case, movers' average wage in the origin sector (relative to the mean wage in that sector) is -0.18. When the skill premium disappears, this difference in the average wage increases to -0.0368. In the baseline parametrization, those who change sectors are unlikely to be skilled; as a result, on average they have much lower wages in the sector they leave. Removing the skill premium removes this initial difference.

Similarly, the skill premium appears to drive the model's ability to match the mean wage of movers at the destination sector. In the baseline case, the log wage gap between movers and the incumbent workers of the destination sector is -0.1786, while this gap decreases to only 0.0003 when $\pi = 0$. The same intuition applies here.

Table 5: Impact of Skill Premium and Sectoral Shocks

Moments	*BM*	*No skill premium* ($\pi = 0$)	*No sectoral shock* ($\sigma_z = 0$)
mobility	0.0677	0.2745	0.0678
volatility of sectoral employment	0.0058	0.0202	0
repeat mobility	0.2633	0.2844	0.2636
movers wage at destination	-0.1786	0.0003	-0.1786
annual wage growth of recent movers	0.0310	0.0003	0.0311
wage of movers at their origin	-0.2172	-0.0294	-0.2171
correl. of life-time earnings and mobility	-0.1854	-0.0112	-0.1823

Notes: This table evaluates the impact of human capital accumulation skill premium and the sectoral shock on the relationship between wages and mobility. The column denoted by *BM* summarizes the predictions of the benchmark model. The other columns correspond to the specific restrictions considered in each experiment.

Section 2 presents a novel fact: lifetime earnings and mobility are negatively correlated. According to Table 5, the skill premium plays an important role in this correlation. When $\pi = 0$, the correlation between lifetime earnings and mobility increases from -0.19 to -0.01. That is, there is almost no correlation between lifetime earnings and mobility. In the baseline case, movers are primarily the unskilled and thus more likely to remain unskilled; as a result, the more mobile have lower lifetime earnings. This link is broken when we impose the restriction $\pi = 0$ on the benchmark model.

This is not to say that one cannot capture the negative correlation between lifetime earnings and mobility in the absence of the skill premium. Section 6, for example, considers a model with no skill premium but with a very persistent process for the mismatch shock. This version is still able to generate the observed negative correlation between lifetime earnings and mobility.

5.2 Decomposing wage growth

The ability to disentangle several factors contributing to the wage tenure relationship represents an important contribution of our analysis. In this section, we further decompose the wage growth of recent movers into two factors: the skill premium and mismatch shocks.

5.2.1 Decomposition

Consider the following experiment. Suppose that a fixed number of workers is forced to change sectors at the beginning of time t and further mobility among them is prohibited. For simplicity, let their average initial shock be zero. The average wage of these workers increases over time due to skill accumulation. Specifically, normalizing their initial wage (at time t) to zero, the average wage of these individuals at time $t+n$ is

$$\overline{w}_n = (1-(1-p)^n)\pi, \tag{18}$$

where $n \in \{0, 1, 2, \cdots\}$. That is, $(1-p)^n$ represents the probability of entering period n unskilled, and $1-(1-p)^n$ is the probability of becoming skilled in period n.

Given equation (18), growth in average wages among these workers, between the periods n and $n+1$, is $p(1-p)^{n-1}\pi$. Then, the average wage growth in the first $n > 1$ years is

$$\gamma_n = \frac{(1-(1-p)^{n-1})\,\pi}{n-1}. \tag{19}$$

Given the calibrated values of p and π, equation (19) implies that the annual average wage growth during the first five years is $\gamma_5 = 0.0241$. This represents the portion of growth in average wages due exclusively to the skill premium.

In the baseline model, annual growth in average wages during the first five years is $\gamma_5^{\mathrm{BM}}= 0.0310$. This means that more than 20 percent ($=100\% \times(1-\gamma_5/\gamma_5^{\mathrm{BM}})$) of the observed wage growth of recent movers is due to the sectoral and mismatch shocks. This also represents a contribution to wage growth unobservable by an econometrician. That is, ignoring the persistent mismatch shock (and corresponding excess mobility) generates a large upward bias in the impact of skill accumulation. Indeed, in Section 6 we show that in a model with no skill premium, a sufficiently persistent mismatch shock generates the observed level of wage growth among movers.[10]

As stated earlier, to measure the wage gap between movers and stayers in the PSID, a sectors are defined as manufacturing and service.[11] These two imply a relatively broad definition of sectors. Others have emphasized occupations (Kambourov and Manovskii (2009b)), jobs and careers (e.g., Neal (1995); Parent (2000); Pavan (2011)) as the key definition of the "sector" to which the skill accumulation is specific. Thus our quantitative analysis ignores the effects along these important dimensions. The key message here, however, is that regardless of the definition of a sector, ignoring persistent worker-sector mismatch shocks (and the resulting excess mobility) leads to substantial bias in estimates of the sector-specific skill premium (also see Section 6).

5.2.2 The cost of exogenous separation

Finally, the results above have implications for measuring the "value" of a job. Topel (1991) uses his estimate of the skill-premium to measure the cost of an exogenous separation. Specifically, Topel (1991) concludes that a worker with 10 years of experience in a particular sector experiences a wage drop of around 25 percent. In the analysis of Topel (1991), the loss upon separation is driven entirely by the skill-premium. Our analysis allows for a similar exercise; however, it provides a decomposition of what is lost upon exogenous separation. An exogenous separation causes a loss of the skill premium *and* the value of the "quality" of the match. The quality of the match is driven by the worker-sector mismatch shock. A worker with longer tenure remains more likely to have a value of x that makes them particularly well-suited to the current sector. Exogenously dissolving the match implies the worker loses

[10] **??** also shows how an increase in the persistence of the mismatch shock raises wage growth among movers.

[11] Lee and Wolpin (2006) also consider these two sectors.

the value of this match quality.

The results above imply the following for the value of a job. Consider a worker with 5 years experience, say, in sector 0. If exogenously separated, the worker experiences a decrease in wages of approximately 17 percent. Of this, approximately 13.5 percent results from the loss of sector-specific skills. The remaining 3.5 percent results from a loss of match quality. This further suggests that dynamic worker-sector mismatch represents an important component of the value of a job.

The key point here is that the value of a job is measured relative to the value of a job of an average person just arriving at the sector (i.e., sector 0). Therefore, if we restrict an exogenously separated worker to work in the other sector (i.e., sector 1), the loss induced by such separation is much higher than the wage gap between new and incumbent workers.

5.3 Sectoral shock and wage growth

The benchmark model has two shocks: a sectoral shock that affects all workers in the same sector, and a mismatch shock. In this section, we simulate model with no sectoral shock (i.e., $z = 0$). The last column of Table 5 summarizes the results.

With $z = 0$, the results remain almost identical to the baseline case. Of course the model does not generate volatility in sectoral employment, but all other moments are virtually unchanged in this case. This suggests that excess mobility remains key to understanding the patterns of wages and mobility. While incorporating the sectoral shock helps us identify and calibrate the dispersion of the mismatch shock, σ_x, it does not drive our main results on the wage-tenure relationship. This is in contrast to much of the literature that has focused on net mobility driven by sector-specific shocks.

6 Role of the Match Shock

The dynamic worker-sector mismatch shock represents a key innovation of this paper. We now examine what role its inclusion plays in capturing the mobility and wage relationships in Table 4. Specifically, we show that by appropriately choosing the parameters of the mismatch shock (σ_x and ρ_x), the model still captures the wage growth of recent movers, the negative wage gap between movers and stayers, and the negative correlation between life-time income and individual-level mobility.

To illustrate this quantitatively, the model is *re-calibrated* with π and p equal to zero. To further emphasize the role of the mismatch shock, the moving cost is set to zero. The parameters σ_x and ρ_x are re-calibrated targeting excess mobility and employment volatility (or, equivalently, net mobility) while holding the discount factor, β, the aging probability δ, and the parameters of the sectoral shock, σ_z and ρ_z, at their benchmark values.

In Table 6, the column labeled "*Re-calibration*" summarizes the results. The re-calibrated model performs reasonably well in replicating the main wage patterns, namely wage growth among recent movers and the negative wage gap between movers and stayers at both the origin and destination.

However, there are three undesirable features/issues. First, the restricted version cannot generate a substantial amount of repeat mobility.[12] Second, although it generates a negative correlation between life-time earnings and individual-level mobility, the correlation is almost twice as high as that in the data, in absolute terms.

Finally, the model requires an implausibly high dispersion of the match shock. The dispersion of the match shock relative to the mean wage is $\sigma_x = 0.4840$. Using the sample of white males aged 18-64 in Current Population Survey (CPS) from 1980 to 2009, we calculate that the standard deviation of

[12] Using an alternative calibration strategy, this specification can generate sufficient repeat mobility. Doing so requires a lower variance of the mismatch shock, σ_x. We have calibrated the model under this alternative for σ_x, and the results are presented in Table B.3 in Appendix B.2. As the table displays, this alternative parametrization is dominated by the one presented above.

Table 6: Role of the Match Shock

Parameters and Moments	*Data*	*Re-calibration*
	Parameters of the match shock	
dispersion, σ_x		0.4840
persistence, ρ_x		0.9553
	Moments	
mobility	0.0678	0.0678*
employment volatility (net mobility)	0.0059	0.0059*
repeat mobility	0.2729	0.0880
movers wage at destination	-0.1786	-0.1649
annual wage growth of recent movers	0.0259	0.0234
wage of movers at their origin	-0.1803	-0.2838
correlation of life-time earnings and mobility	-0.1523	-0.1889

Notes: The table shows the results of the re-calibration that omits sector specific human capital and the sector-switching cost. Specifically, the parameters of the match shock, σ_x and ρ_x, are re-calibrated by targeting certain features of mobility data while setting π, p and c to zero and holding the discount factor, β, the aging probability, δ, and the parameters of the sectoral shock, σ_z and ρ_z, at their benchmark values. * indicates the targeted mobility moments. The column labeled *Re-calibration* refers to the moments in the re-calibrated model.

the residual log wages unexplained by age and education is approximately 0.63. So, according to this restricted calibration, residuals of a standard Mincerian regression would be attributed mainly to the sectoral mismatch shock. This is likely implausible given that the model abstracts from many other wage determinants, such as regional, occupational and firm-level factors. Also, the persistence of this shock, $\rho_x = 0.9553$, is higher than other estimates in the literature (e.g., Guvenen, 2009).

Despite these issues, the results presented in this section show that the worker-sector mismatch shock plays an important role in capturing the key relationships between mobility and wages. This further motivates our attempt to quantify the impact of such shocks on the wage-tenure relationship in an economy with both net and excess mobility.

7 Conclusion

According to PSID data, wages increase with sector-tenure, wages of movers are on average lower in their origin sector, and lifetime earnings is negatively correlated with mobility. A dynamic model is developed to explain these facts. The results imply that sector-specific skill accumulation and mismatch shocks (specific to the worker-sector match) drive the fit of the model. Furthermore, ignoring the mismatch shock biases the estimated sector-specific skill premium. Specifically, ignoring the persistence of the worker-sector mismatch shock (ρ_x) causes an upward bias in the estimated sector-specific skill premium. Finally, the impact of sectoral shocks and net mobility is relatively small, while excess mobility plays the key role for both mobility and wages.

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A Data Appendix

This appendix provides additional details on mobility and wages using the main PSID sample considered in Section 2.

Table A.1 shows that mobility is higher among the younger workers. Figure A.1 illustrates that the negative correlation between mobility and wages remain robust even after controlling for a set of effects including the age of the labor force. Table A.2 presents the results of the OLS regressions of log real hourly wage on a dummy for industrial mobility, along with various combinations of controls. Controlled effects include full sets of dummies for age, education, year, state, current and previous industries and sector tenure. We also consider cases with individual fixed effects. These results indicate that mobility is associated with significantly lower wages. However, the estimated coefficient is very unlikely to be causal, as uncontrolled unobserved heterogeneity is very likely to be correlated to individuals' propensity to move. Moreover, comparing the columns, one can see that sector tenure and individual-specific unobserved effects are both important for the wage-gap between movers and stayers.

Table A.3 shows the evolution of the quantile of wages by sector tenure. Specifically, it reports the quantile values associated with Figure 1. The detailed description of constructing these quantiles are provided in Section 2.3. The quantile values are also plotted in Figure A.1.

Finally, Table A.4 shows that inaccurate measure of mobility in the main PSID sample (also see Kambourov and Manovskii (2008)) results in a weaker correlation between mobility and earnings.

Table A.1: Mobility by Age and Education

Age	*Educational attainment (grades)* ≤4	5-7	8-11	12-15	16≤	all
20-24	0.000	0.188	0.207	0.164	0.197	0.178
	3	32	646	1,562	239	2,482
25-29	0.000	0.193	0.133	0.107	0.093	0.110
	3	88	753	2,422	894	4,160
30-34	0.200	0.119	0.065	0.056	0.039	0.057
	10	134	751	1,687	775	3,357
35-39	0.077	0.087	0.064	0.047	0.032	0.052
	65	207	846	1,286	534	2,938
40-44	0.054	0.041	0.046	0.048	0.032	0.044
	129	268	917	1,228	498	3,040
45-49	0.048	0.049	0.034	0.027	0.011	0.030
	166	348	903	1,163	471	3,051
50-54	0.041	0.070	0.026	0.027	0.016	0.032
	219	356	800	922	368	2,665
55-59	0.039	0.064	0.045	0.025	0.014	0.037
	206	298	606	673	220	2,003
60-65	0.041	0.057	0.061	0.047	0.007	0.050
	145	246	558	529	136	1,614
all	0.048	0.072	0.073	0.072	0.050	0.068
	946	1,977	6,780	11,472	4,135	25,310

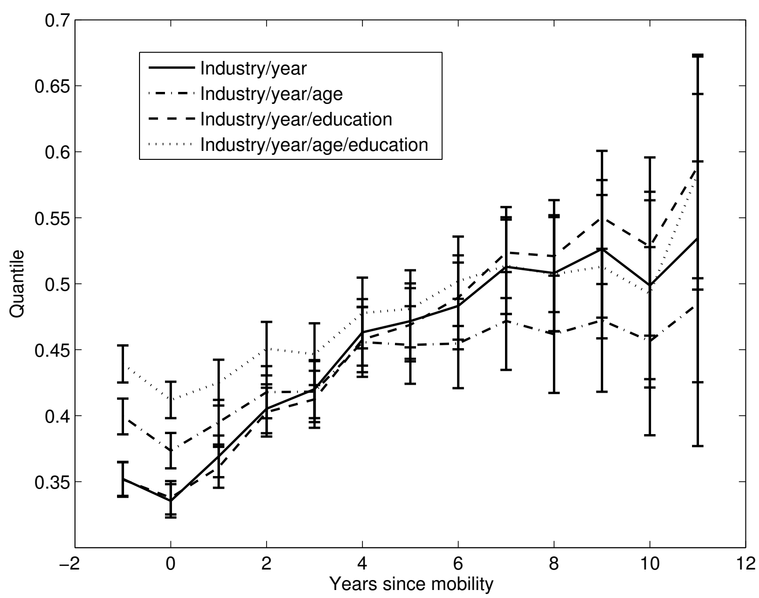
Notes: Each age-and-education cell has two entries: the mobility rate (top) and the number of observations (bottom).

Table A.2: Wage Regressions

Variables	*Specifications*		
mobility dummy	-0.391	-0.095	-0.067
	(0.019)	(0.014)	(0.021)
age, education, year, state, sectors		✓	✓
sector tenure			✓
individual fixed effects		✓	✓
R-squared	0.029	0.761	0.762

Notes: The table shows the results of the wage regressions with various specifications. Clustered standard errors are in parenthesis. The sample consists of 3057 individuals and 25310 year-person observations.

Figure A.1: Wages and Sector Tenure



Notes: The figure shows the evolution of wages after sectoral mobility. It plots the mean wage quantiles along with the 95 percent confidence interval. The values at -1 refer to the wage quantiles of the year before mobility. The labels show which variables are controlled for.

Table A.3: Wage Quantiles by Tenure

Years	*Control variables*				*N*
	industry year	industry year age	industry year education	industry year age education	
-1	0.352 (0.270)	0.399 (0.284)	0.352 (0.274)	0.439 (0.295)	1,715
0	0.335 (0.266)	0.374 (0.283)	0.338 (0.267)	0.412 (0.292)	1,715
1	0.369 (0.264)	0.395 (0.282)	0.361 (0.259)	0.425 (0.290)	1,075
2	0.405 (0.26)	0.417 (0.277)	0.403 (0.260)	0.451 (0.285)	767
3	0.420 (0.272)	0.418 (0.286)	0.412 (0.268)	0.447 (0.290)	594
4	0.463 (0.274)	0.456 (0.286)	0.458 (0.269)	0.478 (0.291)	458
5	0.472 (0.278)	0.454 (0.287)	0.469 (0.271)	0.481 (0.286)	371
6	0.481 (0.278)	0.453 (0.285)	0.487 (0.270)	0.500 (0.286)	278
7	0.513 (0.267)	0.471 (0.276)	0.524 (0.257)	0.512 (0.273)	216
8	0.509 (0.278)	0.463 (0.282)	0.522 (0.268)	0.508 (0.275)	157
9	0.529 (0.269)	0.475 (0.281)	0.551 (0.260)	0.515 (0.280)	104
10	0.510 (0.288)	0.465 (0.291)	0.539 (0.274)	0.501 (0.291)	65
11	0.535 (0.270)	0.485 (0.267)	0.589 (0.210)	0.584 (0.219)	26

Notes: The values at -1 refer to the wage quantiles of the year before mobility. Standard deviations are in parenthesis. N denotes the number of observations.

Table A.4: Wage-Mobility Relationship in Different Samples

	Restrospective Files 1968-1980	Retrospective Files and PSID 1968-1997
$\mathrm{corr}(\mathcal{M}^{\mathrm{a}}, \mathcal{E}^{\mathrm{c}})$	-0.141	-0.105
$\mathrm{corr}(\mathcal{M}^{\mathrm{b}}, \mathcal{E}^{\mathrm{c}})$	-0.152*	-0.104
$\mathrm{corr}(\mathcal{M}^{\mathrm{c}}, \mathcal{E}^{\mathrm{c}})$	-0.168	-0.106
$\mathrm{corr}(\mathcal{M}^{\mathrm{d}}, \mathcal{E}^{\mathrm{c}})$	-0.172	-0.108

Notes: This table shows how the correlation of life-time earnings (measured by $\mathcal{E}^{\mathrm{c}}$) and various measures of individual-level mobility ($\mathcal{M}$) differ between the samples. Specifically, it shows that including inaccurate measure of mobility in the main PSID sample (also see Kambourov and Manovskii, 2008) results in a weaker correlation between mobility and earnings. The above measures of mobility and life-time earnings are defined in Section 2. The asterisk indicates the targeted value.

B Model Appendix

This section provides some robustness checks for the baseline parameterization. It also demonstrates the role of the key elements of the model.

B.1 Sensitivity to sectoral-level productivity shock

In Section 4, the persistence and standard deviation of the sectoral shock, ρ_z and σ_z, are calibrated using the relative productivity series of the manufacturing sector of 1987 to 2012. One could argue that the length of this productivity series may not be sufficient enough to precisely measure the volatility of the sectoral shock. To address this issue, we re-scale the two parameters using much longer aggregate productivity data of 1947 to 2012. For this purpose, let $\rho^{\mathrm{L}}_{\mathrm{agg}}$ and $\sigma^{\mathrm{L}}_{\mathrm{agg}}$ be the persistence and standard deviation of aggregate US productivity in the long sample (i.e., those of 1947 to 2012). Also, let $\rho^{\text{S}}_{\text{agg}}$ and $\sigma^{\text{S}}_{\text{agg}}$ be the persistence and standard deviation of aggregate US productivity in the short sample (i.e., those of 1987 to 2012). Then, one can consider the following re-scaling:

$$\begin{cases} \rho^{\text{L}}_z = \rho^{\text{S}}_z \times \dfrac{\rho^{\text{L}}_{\text{agg}}}{\rho^{\text{S}}_{\text{agg}}}, \\ \sigma^{\text{L}}_z = \sigma^{\text{S}}_z \times \dfrac{\sigma^{\text{L}}_{\text{agg}}}{\sigma^{\text{S}}_{\text{agg}}}, \end{cases} \tag{B.1}$$

where ρ^{S}_z and σ^{S}_z are the persistence and standard deviation of relative productivity of the manufacturing sector obtained using the short sample (i.e., the sample of 1987 to 2012 used in benchmark calibration). These equations imply a slightly more volatile, but less persistent, shock where $\rho^{\text{L}}_z = 0.3683$ and $\sigma^{\text{L}}_z = 0.0090$.

The calibration details under this sectoral shock are shown in Table B.1. Table B.2 summarizes the key predictions of the model. The results indicate that both the parameters and model predictions do not differ much than those in the benchmark model in Section 4.

B.2 Alternative parametrization: the match shock

Section 6 provides a re-calibration of the baseline model under the parametric restriction that $\pi = 0$, $p = 0$ and $c = 0$. The results presented in Table 6 refer to the re-calibration targeting excess mobility and the relative employment volatility. In Table B.3, the results are presented in the second column, labeled "*high* σ_x." An alternative parametrization is given in the third column, labeled "*low* σ_x." This calibration targets excess and repeat mobility. Indeed, with a

Table B.1: Parameters

Parameters	*BM*	*Under renormalized sectoral shock*	*Description*
β	0.9615	same	the time discount factor
δ	0.0250	same	the probability of retirement
p	0.0833	same	the probability of becoming skilled
ρ_z	0.4236	0.3683	the persistence of the sector shock
σ_z	0.0068	0.0090	the volatility of the sector shock
ρ_x	0.4593	0.4547	the persistence of the mismatch shock
σ_x	0.1229	0.1628	the dispersion of the mismatch shock
c	0.0191	0.0279	the mobility cost
π	0.3288	0.3619	the skill premium

Notes: The table summarizes how the key parameters of the model responds to volatility of the sectoral shock. The column denoted by *BM* refers to the benchmark model.

Table B.2: Predictions under Renormalized Sectoral Shock

Moments	*Data*	*Model*
Targeted moments		
mobility	0.0678	0.0677
volatility of sectoral employment	0.0059	0.0059
repeat mobility	0.2729	0.2614
movers wage at destination,	-0.1786	-0.1786
Key predictions		
wage growth of recent movers	0.0259	0.0312
wage of movers at their origin	-0.1803	-0.2309
correlation of life-time earnings and mobility	-0.1523	-0.1731

Notes: The table summarizes predictions of the model under the more volatile sectoral shock considered in the third column (labeled *"Under renormalized sectoral shock"*) of Table B.1.

Table B.3: Role of the Match Shock: Alternative Parametrization

	data	high σ_x	low σ_x
Parameters of the match shock			
dispersion, σ_x		0.4840	0.0188
persistence, ρ_x		0.9553	0.9779
Moments			
mobility	0.0678	0.0678*	0.0646
employment volatility (net mobility)	0.0059	0.0059*	0.1626
repeat mobility	0.2729	0.0880	0.1118*
movers wage at destination	-0.1786	-0.1649	-0.0067
annual wage growth of recent movers	0.0259	0.0234	0.0007
wage of movers at their origin	-0.1803	-0.2838	-0.0112
correlation of life-time earnings and mobility	-0.1523	-0.1889	-0.0084

Notes: The table shows the results of the re-calibration that omits sector specific human capital and the sector-switching cost. * indicates the targeted mobility moments. The column labeled "high σ_x" refers to the version of the model where gross and net mobility are targeted. (The results in this column are the same as those presented in the last column of Table 6.) The column labeled "low σ_x" refers to the version of the model where gross and repeat mobility are targeted.

relatively low value for σ_x, the model can capture repeat mobility; however, this parameterization does significantly worse on the remaining un-targeted moments.

B.3 Ignoring the match shock

In this appendix, we perform another exercise to emphasize the role of the mismatch shock. In particular, we ask what happens if we let the sectoral shock drive gross mobility. In essence, this is a simplified version of Kambourov and Manovskii (2008). Ideally, one would solve the model by setting the dispersion

Table B.4: Parameters Under Low Dispersion of Mismatch Shock, σ_x

Parameters	*BM*	*Low σ_x shock*	*Description*
ρ_x	0.4593	0.4640	the persistence of the mismatch shock
σ_x	0.1229	0.0246	the dispersion of the mismatch shock
c	0.0191	0.0035	the mobility cost
π	0.3288	0.2522	the skill premium

Notes: The table summarizes the key parameters of the model when most of gross mobility is driven by the sectoral shock. The column denoted by *BM* refers to the benchmark model. The parameters β, δ, p, ρ_z and σ_z are as in the benchmark model.

of the mismatch shock σ_x to zero. However, the discrete state space used to solve the model delivers highly unstable solution as σ_x approaches zero. For this reason, we solve the model by setting the dispersion of the mismatch shock σ_x to one fifth of its benchmark value, 0.0246. Table B.4 shows the model parameters under this low σ_x. The associated moments are shown in Table B.5. The key difference between the benchmark model and the model with low σ_x is that the latter model exhibits five times higher employment volatility. So, ignoring the mismatch shock will lead to overly high employment volatility (thus, high net mobility) when the sectoral shock is replicated using the U.S. manufacturing data.

Table B.5: Predictions Under Low Dispersion of Mismatch Shock, σ_x

Moments	*Data*	*Model*
Targeted moments		
mobility	0.0678	0.0677
repeat mobility	0.2729	0.2652
movers wage at destination,	-0.1786	-0.1786
Key predictions		
volatility of sectoral employment	0.0059	0.0298
wage growth of recent movers	0.0259	0.0299
wage of movers at their origin	-0.1803	-0.1862
correlation of life-time earnings and mobility	-0.1523	-0.1699

Notes: The table summarizes predictions of the model when most of mobility is driven by sectoral shock, i.e., under the parametric restrictions shown in Table B.4.