A Directed Search Model of Occupational Mobility*

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Abstract

There has been considerable interest in the patterns of occupational mobility and their effect on various economic issues. In this paper, I utilize the unique interview structure of the longitudinal SIPP to uncover additional interesting facts on occupational mobility. I find that occupational behavior exhibits strong persistence not only among employed workers but also among non-employed workers; occupational switchers do not always switch to an occupation similar to their previous one; and the average length of transition duration workers spend before taking a new stable job varies with their previous occupation. Motivated by theses facts I build a directed search model of occupational mobility, which includes both aggregate and idiosyncratic shocks, and features occupational human capital as well as search frictions. The model can account for the bulk (around 70%) of the patterns in the data and can match reasonably well the emphasized facts. The model is used to study (i) the importance of idiosyncratic vs. aggregate shocks, and (ii) the barriers to occupational mobility. I find that idiosyncratic shocks are the main determinant of occupational mobility whereas aggregate shocks are unimportant. Further, fixed mobility costs and search frictions constitute significant barriers to mobility while the transfer loss of occupational human capital is only of modest importance quantitatively.

Keywords: Occupational Mobility, Directed Search, Idiosyncratic Shock, Aggregate Shock, Mobility Costs, Search Frictions

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1 Introduction

Recent economic studies demonstrate an important role the occupational mobility plays in accounting for various interesting economic issues. For instance, Kambourov and Manovskii (2009) calibrate a model to match the level and the change of occupational mobility and it accounts quite well for the level and the change of within-group wage inequality. Hoffmann (2010) argues that a worker's occupational mobility is of exceptional significance among the worker's labor market mobility dynamics, which determines an individual's life-cycle earnings pattern.

Following Keane and Wolpin's (1997) seminal paper on young workers' occupational (and educational) choice, most empirical studies take a micro view and focus on matching a model to the individual choice pattern in the data.[1] The model usually has a very large number of parameters to pin down, to achieve a perfect fit to the data. Therefore, it's not very easy to distinguish the relative importance of each parameter and to understand what role each factor plays, due to the complicated correlations and interactions among parameters. This paper looks at data from a macro perspective with the focus on the aggregate mobility patterns, in an attempt to address 2 questions: on the one hand, what are the main determinants that induce/generate the aggregate occupational mobility; on the other, what are the major barriers to the mobility. In building a parsimonious model which contains only a small set of variables, it is relatively easy for me to identify the key factors and to find out the answer.

In this paper, I utilize the unique interview structure of the longitudinal Survey of Income and Program Participation (questions about occupations and other employment information every 4 months) to uncover additional interesting facts on occupational mobility. Specifically, I examine 5 broad occupational aggregates (Professional, Technical, Service, Craft, and Operators) and study in detail the mobility patterns among them. The 4 facts are generally descriptive of 2 aspects of people's occupational behaviors. The first aspect concerns workers' choice "direction": Given an individual's original occupation (and other characteristics), what occupation (could be the same as the original one) does the person select to work in. I calculate flow distributions across occupations and labor market statuses, denoted as the mobility distributions, from data and stress 3 salient patterns regarding mobility distributions. The second aspect is related with the transition time between a worker's 2 occupations (again, they could be the same). The

[1] See, for example, Sullivan (2010) and Hoffmann (2010).

transition time is defined as a period during which a worker is unemployed, not in the labor force, working part-time, or working full-time in a transitory job. It is a generalization of the concept of non-employment (unemployment and/or not in the labor force) in the context of occupational mobility. Obviously, the length of transition time contains useful information on ease of entry into a particular occupation. I calculate transition time distributions for various source occupations and point out one important feature of this class of distributions.

In particular, I find that occupational behavior exhibits strong persistence not only among employed workers but also among workers in transition; a worker becomes less likely to switch occupation with the increase in occupational human capital; occupational switchers do not always switch to an occupation similar to their previous one; and the average length of transition duration varies with their previous occupation.

Research that involves occupational mobility often makes use of 2 prototypical models: Lucas and Prescott (1974) and Keane and Wolpin (1997), with the former a search model and the latter a dynamic discrete choice model with no search frictions. Casual observation reveals that when an individual faces occupational choice, he or she considers pros and cons in each candidate occupation and makes the decision to maximize his or her personal interests. This is the basic feature of a discrete choice model. And to be shown soon, among the facts this paper tries to address, some are related with the unemployment spell, or more accurately, the transition duration. Search models are usually used to account for unemployment, among other labor market phenomena. Therefore, each of the 2 models has a main merit which makes it suitable for modeling certain aspects of the occupational mobility. The current paper combines one with the other.

Motivated by the facts found in data, I construct a directed search model, taking the advantages of a search model and a discrete choice model. Unlike in Lucas and Prescott (1974) where all unemployed workers apply for all jobs with a positive probability (go to all the submarkets with a positive probability[2]), workers in my model observe all the relevant variables in each occupation, and given their individual characteristics, most importantly their current occupation (or latest one if unemployed) and occupational human capital, apply to only one occupation, the one which brings them the most benefits. In Keane and Wolpin (1997), unemployment is denoted as home production, which is a worker's voluntary choice. While in the current pa-

[2]More accurately, not all the submarkets see newcomers: the submarkets experiencing a very bad shock don't attract unemployed workers.

per, unemployment (or more accurately, transition) is caused by exogenous separation and search frictions, and is thus involuntary.

The model includes both aggregate and idiosyncratic shocks. The aggregate shock affects a set of occupation-specific variables: job-finding rates, displacement rate, and occupational returns. They jointly characterize an individual occupation and are key to workers' decision-making, and are well known to all the agents. The idiosyncratic shock is used to capture nonpecuniary factors that affect an individual's occupational choice and turns out to be of exceptional importance.

As in Keane and Wolpin (1997), human capital is included in the model. However, what's different here is that occupational human capital is not strictly occupation-specific as in a typical Roy-type model. Instead, it is partially transferable across occupations, and the transferability depends on the similarity between 2 occupations. I apply the task-based approach used in Gathmann and Schonberg (2010) to measure the distance between a pair of occupations. In this sense, the occupational human capital in the paper is general as well as occupation-specific. The transfer loss of human capital apparently constitutes an obstruction to the occupational mobility. But as numerical exercise shows, quantitatively, it is not very significant. Sullivan (2010) also contains both human capital and occupational mobility in his model, and his main purpose is to compare the importances of the two in accounting for workers' earnings and lifetime utility. In this paper, I find the two factors are interrelated: removing the transfer loss of human capital will lead to an increase in occupational mobility.

The model is solved numerically. In particular, I calibrate the model to match exclusively the mobility distributions. And it turns out that the model can also account for a large fraction of transition time distributions. In all, it explains 65% of the former and 76% of the latter. Furthermore, the model can match reasonably well the emphasized facts. The model is used to study (i) the importance of idiosyncratic vs. aggregate shocks, and (ii) the barriers to occupational mobility. I perform numerical experiments by removing the relevant variables, one at a time, from the model and examine how the model performs. I find that idiosyncratic shocks are the main determinant of occupational mobility whereas aggregate shocks are unimportant. Further, fixed mobility costs and search frictions constitute significant barriers to mobility while the transfer loss of occupational human capital is only of modest importance quantitatively.

My work also contributes to the fast-growing directed search literature.[3]

[3]See, for instance, Moen (1997) and Menzio and Shi (2011).

It's novel to study the occupational mobility in a directed search framework. And in solving the model, I obtain a set of estimates of occupation-specific job-finding rates. To my knowledge, there does not exist estimates of this kind in the literature. Search frictions are important in generating unemployment to unemployment transitions, or more accurately, transition to transition mobility in this paper.

The rest of the paper is organized as follows. Section 2 introduces some key concepts of the paper and applies them in the wage regression. Section 3 documents the stylized facts found in the data. Section 4 describes the model. In Section 5, I do the calibration and numerical experiments. Conclusions are in the last section.

2 Distance between Occupations and General Occupational Tenure

In this section, a measure to determine the distance between a pair of occupations is introduced. Associated with the measure, is the Transfer Rate, or the fraction of occupational human capital that is transferable across occupations. Accordingly, a new relevant tenure variable, the General Occupational Tenure, is used to measure occupational human capital in this context.

2.1 Occupations and Occupational Classification under SIPP

Occupation is a name or title that is assigned to a certain class of work duties an individual performs. In general, people group jobs of similar work content, job tasks, and skill requirements to a single occupation title. There exist many such occupational classifications, with the most popular ones: the Standard Occupational Classification (SOC), the Dictionary of Occupational Titles (DOT) and the Occupational Network Database (O*NET). They classify occupations and give detailed descriptions and qualifications to each occupation. All of them take a hierarchy structure: a large number of narrowly defined occupations are grouped into a smaller number of broader occupational aggregates, and they are further categorized into a even smaller number of higher level occupational aggregates, and this process may proceed further, depending on an individual classification system's design.

This paper makes use of the data from the Survey of Income and Program Participation (SIPP). SIPP is designed by the U.S. Census Bureau to collect detailed information on income, employment, and government transfer programs participation of the U.S. civilian noninstitutionalized population. It selects a nationally representative sample of households and interviews them in every 4 months (called a wave). The high interview frequency is very advantageous to me in that I can observe a worker's occupational mobility within a year. SIPP is administered in the so-called panels, and each panel is a new sample. I use SIPP's 1996 panel (SIPP96 henceforth) which spans from December 1995 to February 2000 and covers a total of 95398 respondents,[4] one of SIPP's largest samples.

SIPP96 utilizes the U.S. 1990 Census Occupational Classification System, which in turn builds upon the SOC 1980 version. SIPP96's occupation table consists of 501 finest titles, which are grouped into 13 major groups and finally 6 summary groups. Constrained by the computational capacity, I use the highest level aggregates, the 6 occupational summary groups (1-digit occupations). But the proposed framework and methodology can in principle be applied to any level of occupational classification, and are hence general. Due to the special nature of farming related occupations, they are not considered in the paper. So a classification of 5 broad occupations is used as follows:

1.Managerial and Professional Specialty Occupations, and henceforth Professional for short.

2.Technical, Sales, and Administrative Support Occupations, and henceforth Technical for short.

3.Service Occupations, and henceforth Service for short.

4.Precision Production, Craft, and Repair Occupations, and henceforth Craft for short.

5.Operators, Fabricators, and Laborers, and henceforth Operators for short.

2.2 Distance between Occupations and General Occupational Tenure

Intuitively, when a worker changes occupations, he or she usually incurs some loss of occupational human capital. This is because each occupation has its specific requirements of knowledge, skill, and proficiency. When a worker switches between a pair of occupations of very different requirements,

[4]The actual data come from a subsample of SIPP96. The main restrictions include: male, aged between 18 and 64, not disabled, and not self-employed. And the size of effective sample is 26421.

the loss is heavy, or equivalently, the fraction of occupational human capital that can be transferred is small. It's no wonder when a recruiter interviews a job candidate, an inevitable question is: Do you have any experience in this field? Only the experience in the interviewed occupation or in a close one is of interest, and the experience in a distant occupation does not really matter.

Though intuitive, it is not easy to measure the distance between occupations in practice. The point of finding such a measure is that it can help quantify the amount of occupational human capital conveyed (or destructed, the other side of a same coin) in an occupational switch. The closer the 2 occupations are , the higher is the Transfer Rate, and the farther, the lesser. I find the measure used in Gathmann and Schonberg (2010) is intuitively appealing and applicably convenient. The measure takes a task-based approach: Each occupation is differentiated by the set of tasks it employs and the degree of intensity of every task deployed. In an occupational space of n tasks, a single occupation is represented by a vector O of n dimensions $(O_1, O_2, \ldots, O_n)$, where O_i is the degree of intensity of task i. Strictly speaking, an occupation is a ray that stems from the origin of the vector space and goes through the point corresponds to the aforementioned vector.[5] The distance between 2 occupations is measured by the angle formed by the 2 corresponding rays. The bigger the angle is, the farther the 2 occupations are from each other. With all the elements in an occupation vector to be nonnegative, the distance measure lies in $[0, \pi/2]$. As a demonstration, Figure 1 shows a switch example from Occupation O to Occupation O' in a 2-dimensional vector space (namely, each occupation employs only 2 tasks). In the figure, the angle formed by the source and target occupations, θ measures the distance between the 2 occupations.

When a worker changes occupation from O to O' with the distance $\theta \in [0, \pi/2]$, the Transfer Rate of human capital regarding Occupation O is a strictly decreasing function of θ. Intuitively, this decreasing function appears to be convex: In general, occupational switch stands for a serious change in one's career and is costly. Even when switching to a relatively close new occupation, the loss of occupational human capital is considerable. A large fraction is lost as a consequence of initial deviation from the source occupation, and the impact of further deviations tends to be comparatively small. Empirically, I find the following convexly decreasing function

[5]That is, what matters is the relative intensity across tasks, not the absolute magnitude of intensity indices. Different points on a ray stand for different normalization methods of task intensities for a same occupation.

is satisfactory:

$$TransRate(\theta) = (-\frac{2}{\pi}\theta + 1)^5 \tag{1}$$

As Figure 2 shows, Equation 1 is essentially a convex transformation from a linear function of θ, $f(\theta) = -\frac{2}{\pi}\theta + 1$.[6] When there's no occupational switch ($\theta = 0$), Transfer Rate equals 1, that is, 100% of occupational human capital can be transferred. When the farthest possible switch takes place, Transfer Rate equals 0, namely, nothing is transferable.

Practically, this measure can be computed readily using existing data. Gathmann and Schonberg (2010) offer information on the degree of intensity of 3 basic tasks, manual, analytic, and interactive, to be utilized in 64 occupations (Table A1 in their paper). I aggregate them into my 5 occupations. Table 1 lists pairwise distances and Transfer Rates under the paper's occupational classification. It shows that the closest nonidentical pair is Craft and Operators, and the farthest pair is Professional and Operators, which is in line with our intuitions. In what follows, the array of Transfer Rates in Table 1 is simply called the Transfer Matrix.

2.3 Occupation-Specific Returns

Following convention in the literature, I use tenure to measure the occupational human capital. Because occupational human capital can be partially transferred across occupations in this context, it is general as well as occupation-specific. Whereas in most papers, zero transferability is assumed. Therefore I call the occupational tenure in my paper *General Occupational Tenure* to distinguish the difference. Conceptually, General Occupational Tenure is between the conventional occupational tenure and general human capital, e.g. work experience, with it being broader than the former and narrower than the latter. To apply this new tenure concept in a wage regression, I use a very general framework as follows:

$$\begin{aligned}\log w = {} & \beta_1 I_1 + \cdots + \beta_5 I_5 + \beta_{Edu}\text{Edu} + \beta_{EduSq}\text{Edu}^2 \\ & + \beta_{Exp}\text{WorkExp} + \beta_{ExpSq}\text{WorkExp}^2 + \beta_{Emp}\text{EmpTen} \\ & + \beta_{EmpSq}\text{EmpTen}^2 + \beta_{Ind}\text{IndTen} + \beta_{IndSq}\text{IndTen}^2 \\ & + \beta_{Occ1} I_1 \times \text{GenOccTen} + \cdots + \beta_{Occ5} I_5 \times \text{GenOccTen} \\ & + \beta_{OccSq1} I_1 \times \text{GenOccTen}^2 + \cdots + \beta_{OccSq5} I_5 \times \text{GenOccTen}^2 \\ & + X'B + \zeta \end{aligned} \tag{2}$$

[6] Various Transfer Rate Functions are tried and this one yields the best calibration result. The calibration is discussed in Section 5.

In the above regression, $\log w$ is the natural log of real wage; I_i is the indicator function for Occupation i, and it equals 1 if the worker examined works in Occupation i and 0 otherwise; Edu is a worker's years of schooling; WorkExp, EmpTen, and IndTen are a worker's work experience, employer tenure, and industrial tenure, respectively; GenOccTen is a worker's General Occupational Tenure; and finally X is a vector of indicator functions that control for a worker's race, marital status, region, 1-digit industry, whether being unionized and the interview group[7].

In the wage regression, regressors Edu, WorkExp, EmpTen, IndTen, and GenOccTen take a quadratic form. To solve the endogeneity problem, I exploit SIPP's panel data structure and follow Altonji and Shakotko (1987), using WorkExp, EmpTen, and IndTen's deviations from mean as their instruments. The regression is run in an overlapping manner, every time data from 3 consecutive waves are being used. So each wave's data is to be used for 3 regressions. Please note that GenOccTen is special and I do not instrument for it. Because occupational tenure is transferable in the current framework, a worker's large amount of human capital in his current occupation could result from the fact that he does really well in the occupation, however, it is also possible that he is actually a mediocre praconer in the field but inherits a lot of human capital from his previous occupations. In this sense, the endogeneity coming from occupational match quality is less of the concern. Later in the model part, there does exist an idiosyncratic shock term, but it is irrelevant to match quality and is used to capture something else. And moreover, that shock is independent over time. By interacting occupational dummies with the constant, GenOccTen, and its squared term, occupation-specific intercept, slope, and second order coefficient can be obtained. In combination, they provide information on the returns in a particular occupation.

Table 2 lists the main results for the wage regression. Each column stands for an independent regression, with the title indicating what data are used. For instance, Wave 2 implies that the particular regression is based on data starting from Wave 2, namely, data from Waves 2, 3, and 4.[8] The numbers in the table are estimated coefficients on the regressors, and the regressors are listed in the first column. The stars next to an estimate indicate its significance level, with single star implying 5%, double star 1%, and triple star 0.1%. Number of observations is on the last row.

[7]SIPP divides all respondents into 4 groups and call them rotation groups.

[8]Recall that every regression makes use of data from 3 consecutive waves, and the regression is run in an overlapping manner.

As can be seen in Table 2, coefficients on WorkExp, EmpTen, IndTen and their square terms are in most cases not significant in the presence of General Occupational Tenure, whereas GenOccTen and its square terms are almost always significant for all 5 occupations (except the squared GenOccTen for Occupation 1, Professional). In some sense this is good news. If the wage information is needed in a model, I do not need to keep track of various tenure variables. Instead, only the variable GenOccTen is required, or to be more careful, the education level Edu being added. Table 2 also shows that occupation-specific returns consist of 3 components, the intercept term Ii, the linear term Ii_OccTen×GenOccTen, and the quadratic term Ii_OccTenSq×GenOccTen^2, where $i \in \{1, 2, 3, 4, 5\}$. So for each occupation, the real wage is a quadratic function of the General Occupational Tenure, given a worker's other characteristics. As a worker's General Occupational Tenure increases, his wage rate first goes up, and then reaches the peak and finally declines.[9] Furthermore, among the 3 return terms, the intercept component is much more important than the other 2 terms quantitatively. Take Occupation 2 (Technical) in Regression Wave 2 as an example. Combining the linear and quadratic effects, a worker with 30 years of General Occupational Tenure (the peak time for Technical wage returns) can get a return of 0.406, strictly dominated by the return from the intercept term, 1.385. Figure 3 plots occupation-specific intercepts against time and Table 3 lists coefficient of correlation for pairwise occupational intercept returns. As can be seen, in general the intercept returns of 5 occupations are positively correlated, moving in same directions at all times. Motivated by this feature, I assume there exists an aggregate shock in the economy. The aggregate shock, for simplicity, may take on 2 values: Good (g) or Bad (b). When a good shock hits the economy, the intercept component is higher and hence the entire occupational returns are higher in all occupations, than when a bad shock hits the economy. This issue will be explored further in Section 4.

3 Occupational Mobility Patterns in the Labor Market

In this section, I discuss some key descriptive statistics obtained from SIPP96 and show what stylized facts can be learned from them.

[9] Occupation 1, Professional is an exception, because its second order coefficient is insignificant. So a Professional worker sees his wage increase linearly with his General Occupational Tenure.

3.1 Occupational Mobility Distributions

As mentioned before, mobility distributions concern the flow distributions across occupations and labor market statuses. Figures 4 and 5 depict them graphically. Figure 4 plots all the possible flows for workers who are in transition[10] at time $t-1$, or off-job search workers. At time t, some of them may be employed in the same occupation as their source occupation, namely the latest occupation one works in when he is employed; some may be employed in other occupations; others may continue to stay in transition. Similarly, Figure 5 shows all the possible flows for workers who are employed at time $t-1$, or on-the-job search workers. The potential destinations are identical in Figure 5 as in Figure 4.

To be more concrete, Tables 4 to 7 display workers' occupational mobility distributions for off-job search workers in good time, off-job search workers in bad time, on-the-job search workers in good time, and on-the-job search workers in bad time, respectively. Each table is divided into 2 parts, with the left part under the title "Source" and the right part "Target" or "Result", implying that a worker works in Occupation x at time $t-1$, and works in Occupation y at time t.[11] For off-job search workers, their target occupations can be observed, which are the occupations they work at time t. However, for an on-the-job search worker, although his occupation at time t is known, it might not be his target, because he may have a bad luck and has his application for the desired occupation declined, and thus goes back to the time $t-1$ occupation. Hence in tables for on-the-job search workers, "Result" rather than "Target" is used to show this difference. Furthermore, every table's right part consists of 3 groups of data according to skill levels: low (with the General Occupational Tenure less or equal to 14 years), medium (with the General Occupational Tenure between 14 and 28 years), and high (with the General Occupational Tenure greater than 28 years). Moreover, the 5 columns under each skill level refer to the 5 occupations worked at time t. Depending on their distances from the source occupation, the 5 occupations are listed in the order from near to far, with the leftmost column closest to the source occupation and the rightmost farthest. In combination, Tables 4 to 7 list the flow percentages in each case. For instance, the number "15.19" on the first row in Table 4 indicates that, in good time

[10] Recall that a worker is in transition if he is unemployed, and/or not in the labor force, and/or doing part-time work, and/or doing full-time transitory work.

[11] Strictly speaking, this is the case for on-the-job search workers, who work at both time $t-1$ and time t. For off-job search workers, the table considers that a worker used to be working in Occupation x before time $t-1$ and works in Occupation y at time t.

among off-job search workers with low skill levels who used to be working in Occupation 1 before time $t-1$ and who find jobs at time t, 15.19% of them shift to Occupation 2. Finally, to emphasize, in the tables the dominant flows (greater than 50%) and important flows (greater than 10%) are marked with double stars and single stars, respectively. At this moment, ignore all the data in parentheses. In what follows, I call workers on each row in a table, or equivalently workers who share a same source occupation, a group, and I further call them a subgroup if they share a same source occupation and a same skill level.

From the above tables, I find 3 stylized facts with regard to the occupational mobility distributions:

Fact 1 Workers' occupational behavior demonstrates strong persistence. In other words, the majority of them continue to work in an occupation the same as their previous occupation. As can be seen from Tables 4 and 5, more than half of the off-job search workers continue to work in their source occupation, no matter how skilled they are, regardless of the aggregate economic conditions. This pattern is even sharper for on-the-job search workers. Tables 6 and 7 show that at least 98% of workers in all the subgroups end up with the same occupation in time t as in time $t-1$. Sullivan (2010) reports a similar finding, but only for on-the-job search workers.

Fact 2 As a worker's General Occupational Tenure increases, he becomes less likely to switch to other occupations. This tendency generally holds for workers of all source occupations and under both good and bad aggregate shocks, especially starker for off-job search workers. Take off-job search workers whose source occupation is 1 (Professional) as an example, in good times, 68.57% of them choose a target occupation of Professional when their General Occupational Tenure is less than 14 years; this fraction goes up to 89.74% for those whose General Occupational Tenure is between 14 and 28 years; the percentage continues to climb and 100% of them choose not to switch occupations if we consider only the workers with the General Occupational Tenure greater than 28 years.

Fact 3 For workers who do change their occupations[12], they do not always switch to the closest neighbor occupation. While the groups of occupational switchers with source occupations Professional, Craft, and Operators tend to switch to the nearest occupation, their counterparts with the source occupation Technical are likely to select distant target occupations, and Service workers are inclined to shift to the occupation of middle distance.

[12]The flows that are both qualitatively and quantitatively important are those with a single star in Tables 4 and 5.

3.2 Transition Time Distributions

Mobility distributions alone, however, are not complete in describing the occupational mobility patterns in the labor market. They only consider the workers who hold a job at time t[13]. What's missing here is the pattern for workers who do not work for at least 2 consecutive periods. For these workers, the intervening transition time between the 2 jobs (2 occupations) is a nontrivial statistic.

Table 8 and Figure 6 are informative with regard to the transition time distributions. Table 8 lists the mean transition times for workers of all source occupations under both good and bad aggregate shocks.[14] For each source occupation, numbers on the top row are in the units of waves, the reference period of SIPP interview, where one wave equals 4 months; numbers on the bottom row are the equivalent mean transition times in the units of months, calculated from the top row numbers. For this moment, ignore the numbers in parentheses. Figure 4 graphically demonstrates the transition time distributions across different subgroups and under different aggregate shocks. For this moment just pay attention to Part(a) and ignore Part(b). Each part consists of 10 panels, with the top row depicts situations under good shocks and bottom row bad shocks. The 5 panels on each row, from left to right, correspond to Occupations 1 to 5: Professional, Technical, Service, Craft, and Operators, respectively. The 3 stacked bars in every panel represent 3 different skill levels from left to right: low, medium, and high.[15] Each bar has 3 sections and they, from bottom to top, show the fractions of workers who experience short (4 months), medium (8 months or 1 year), and long (more than 1 year) transition periods, respectively.

According to Table 8 and Figure 6, a fact concerning the transition time distributions is:

Fact 4 The average length of transition time depends on a worker's source occupation, and follows such an order from long to short: Professional, Technical, Service, Craft, and Operators, no matter under what economic conditions. This cross-sectional difference is clear in Table 8. And Figure 6

[13] They may be with or without a job at time $t-1$.

[14] The mean transition times seem much longer than the mean unemployment duration reported in many empirical papers. Recall that I include the time a worker spends on out of the labor force, doing part-time jobs, and doing full-time transitory jobs in the transition. The mean unemployment duration calculated from SIPP96 is 16.21 weeks, consistent with the results reported by other authors.

[15] Recall from Tables 4 to 7 that, a worker is low skilled if his General Occupational Tenure is less than or equal to 14 years, medium skilled if between 14 and 28 years, and high skilled if more than 28 years.

provides more details: The mean transition time is mainly influenced by the fractions of 2 groups of workers: the top end who experience long transition periods and the bottom end who experience short durations. An occupation sees a longer mean transition time than another either because it has more workers in its top end, or because it has less workers in its bottom end; the "middle class" is relatively even across occupations.

3.3 Discussion

The 4 facts extracted from data provide valuable insights for understanding the occupational mobility in the labor market. Fact 1 emphasizes the importance for including occupational stayers, otherwise the picture might be incomplete. Therefore a synthetic approach is appropriate for analyzing workers' occupational behavior: they always aim to maximize individual interests by making the best occupational choice, no matter what they end up to be: occupational switchers or occupational stayers. Yet on-the-job search and off-job search should be distinguished, as a quantitatively big difference can be seen in Fact 1. Facts 2 and 4 indicate that, among an individual worker's many characteristics, his source occupation and General Occupational Tenure are very relevant to his optimal occupational choice. Fact 3 implies that the distance between occupations is an important factor when a worker makes a decision, but may not be the unique factor. The aggregate shocks are motivated by the wage regression results. However, inclusion of only aggregate shocks seems inadequate. Further investigation of Tables 4 to 7 discloses that a same subgroup of workers' optimal choices always differ, indicating that idiosyncratic shocks also matter.

To summarize, in an occupational mobility model, both occupational switchers and stayers are to be considered; but on-the-job search and off-job search should be treated differently; source occupation, General Occupational Tenure, aggregate shocks and individual shocks are significant variables; and distance between occupations is an important factor.

4 The Model

This section describes the model and explains how the results obtained from the wage regression can be used in the model.

4.1 Model Environment

The economy is populated by a large amount of workers, who derive utility only from consumption. Time is discrete. The workers discount future utility at rate $\hat{\beta}$ and die with probability ρ in every period. So the effective discount factor for workers is $\beta = \hat{\beta}(1 - \rho)$. A worker is endowed with a fix number T units of time in each period. There are N occupations in the economy that are indexed by i, where $i \in I \equiv \{1, 2, \ldots, N\}$. If a worker works in Occupation i at time t, his labor income is $w_{it}T$, where w_{it} is the real wage rate in Occupation i at time t. If he is not employed, he receives benefits from the government (not explicitly modeled) with the amount bT, where b is a positive constant. There is no technology of borrowing or saving in this economy, so a worker consumes all his labor income or government benefits in each period, given a strictly increasing instantaneous utility function $u()$. Leisure or labor disutility is not modeled, so a worker seeks to maximize

$$\sum_{t=0}^{\infty} \beta^t u(c_t)$$

where c_t is the worker's autarky consumption at time t.

Human capital is general as well as occupation-specific, and is measured by the General Occupational Tenure. As demonstrated in the wage regression, General Occupational Tenure is the most important determinant of the wage rate, $w_{it} = w(s_{it}, \psi_t)$, where s_{it} is the General Occupational Tenure in Occupation i at time t, and ψ_t is a vector of all the other variables that affect the wage. In the wage regression, they are the vector X_t. General Occupational Tenure is partially transferable across occupations: When a worker switches occupation from i to j, a fraction $\delta_{ij} \in (0, 1]$ of General Occupational Tenure can be carried with the worker, that is, $s_{jt} = s_{it}\delta_{ij}$. δ_{ij} can be large or small, depending on the distance between occupations. The closer the 2 occupations are , the larger is δ_{ij}. A matrix composed of δ's with δ_{ij} being its entry at i's row and j's column is called a Transfer Matrix. Transfer Matrix is symmetric with 1's on its diagonal. General Occupational Tenure s_i increases by τ when a worker works in Occupation i for one period.

Workers meet occupations with search frictions and search is directed. When a worker applies to an occupation, he knows the probability with which he can get a job offer. This probability is called the job-finding rate of that occupation. Job-finding rates are occupation-specific and vary across occupations. For a given occupation, the job-finding rate is different for on-the-job search and off-job search workers, with the rate higher for the former class. In reality, it is usually easier for a job searcher to find work on-the-job than off-job, perhaps due to the difference in social networking, information available, financial resources, so on and so forth. Each period, workers also separate exogenously from work in all occupations. The probability of such exogenous separation is called the displacement rate, and like job-finding rate, it differs across occupations. Therefore, an individual occupation is fully characterized by its wage scheme (most importantly, of General Occupational Tenure), job-finding rates (on-the-job and off-job) and displacement rate. They are well known to all the workers and workers make optimal choice in applying to occupations.

The model period is chosen the same as SIPP's reference period, which is 4 months. Each period has 3 stages, with the first being search and matching stage. At this stage, all on-the-job search workers and eligible[16] off-job search workers send out applications to their target occupations.[17] For a worker applying to Occupation i on-the-job, he succeeds in matching with target occupation with the job-finding rate p_i; for an off-job search worker, his job-finding rate is p'_i, with $p'_i < p_i$. The on-the-job search worker switches to his target occupation if he gets the job offer, otherwise he goes back to his source occupation and matches with it with certainty. The same is for the off-job search worker if he obtains the job offer, but in case of failure, he receives benefits from the government and waits to search off-job again in the next period. At the second stage, production and consumption take place. Matched workers work in their occupations and get paid. All workers consume what they get. At the last stage, matched workers separate with their occupations exogenously with the displacement rate q_i. Those separated cannot search immediately and must stay not employed for one period.

4.2 Value Functions

The economy is assumed to be in the stationary state, and hence all the value functions are without a time subscript. The value function for on-the-job search workers is as follows

$$V(i, s_{it}, \Omega_t) = \max\{V_{stay}(i, s_{it}, \Omega_t), V_{switch}(i, s_{it}, \Omega_t)\} \tag{3}$$

[16]See Stage 3 for details.

[17]This model assumes that all eligible workers search with probability one in a period. Given the length of model period (4 months), this assumption is reasonable. Menzio and Shi (2011) calibrate a directed job search model to the U.S. economy and find that monthly on-the-job search probability is 1 and monthly off-job search probability is 0.833 for all workers.

where,

$$\begin{aligned}
&V_{stay}(i, s_{it}, \Omega_t) = \\
&\quad u(w_{it}T) + \beta(1 - q_{it})\mathbf{E}V(i, s_{it} + \tau, \Omega_{t+1}) + \beta q_{it}\mathbf{E}U(i, s_{it} + \tau, \Omega_{t+1}), \\
&V_{switch}(i, s_{it}, \Omega_t) = \\
&\quad \max_{j \neq i, j \in I} \{p_{jt}[u(w_{jt}T) + \beta(1 - q_{jt})\mathbf{E}V(j, s_{it}\delta_{ij} + \tau, \Omega_{t+1}) \\
&\quad + \beta q_{jt}\mathbf{E}U(j, s_{it}\delta_{ij} + \tau, \Omega_{t+1})] \\
&\quad + (1 - p_{jt})[u(w_{it}T) + \beta(1 - q_{it})\mathbf{E}V(i, s_{it} + \tau, \Omega_{t+1}) \\
&\quad + \beta q_{it}\mathbf{E}U(i, s_{it} + \tau, \Omega_{t+1})] - \phi\}
\end{aligned}$$

in which Ω_t denotes the wage schemes (or the set of variables as well as coefficients in the wage regression) for *all* occupations at time t, $\mathbf{E}$ represents the conditional expectation based on information contained in Ω_t, and ϕ is a fixed mobility cost in terms of utils, which is a one-time cost and is incurred only when a worker prepares to switch occupation on-the-job.

For an off-job search worker, his value function is

$$W(i, s_{it}, \Omega_t) = \max\{W_{stay}(i, s_{it}, \Omega_t), W_{switch}(i, s_{it}, \Omega_t)\} \tag{4}$$

where,

$$\begin{aligned}
&W_{stay}(i, s_{it}, \Omega_t) = \\
&\quad p'_{it}[u(w_{it}T) + \beta(1 - q_{it})\mathbf{E}V(i, s_{it} + \tau, \Omega_{t+1}) \\
&\quad + \beta q_{it}\mathbf{E}U(i, s_{it} + \tau, \Omega_{t+1})] \\
&\quad + (1 - p'_{it})[u(bT) + \beta\mathbf{E}W(i, s_{it}, \Omega_{t+1})], \\
&W_{switch}(i, s_{it}, \Omega_t) = \\
&\quad \max_{j \neq i, j \in I} \{p'_{jt}[u(w_{jt}T) + \beta(1 - q_{jt})\mathbf{E}V(j, s_{it}\delta_{ij} + \tau, \Omega_{t+1}) \\
&\quad + \beta q_{jt}\mathbf{E}U(j, s_{it}\delta_{ij} + \tau, \Omega_{t+1})] \\
&\quad + (1 - p'_{jt})[u(bT) + \beta\mathbf{E}W(i, s_{it}, \Omega_{t+1})] - \phi'\}
\end{aligned}$$

in which ϕ', like ϕ is a fixed mobility cost in terms of utils, which is a one-time cost and is incurred only when a worker prepares to switch occupation off-job.

Finally, for workers who are not employed, or in transition, the value function takes the form

$$U(i, s_{it}, \Omega_t) = u(bT) + \beta\mathbf{E}W(i, s_{it}, \Omega_{t+1}) \tag{5}$$

For an on-the-job search worker with source occupation i and General Occupational Tenure s_{it}, he chooses between to stay or to switch, and to what target occupation j to apply if the latter. If he stays, he earns wage from occupation i, and gets displaced with probability q_{it} at the end of the period. If he elects to switch to occupation j, with probability p_{jt} he gets the job and then works in occupation j to earn labor income, and gets displaced with probability q_{jt} at the end of the period; however, when he fails to get a job offer in his target occupation, he returns to work in occupation i, and later separates exogenously with occupation i with probability q_{it}. Note the evolution of General Occupational Tenure: When transfer happens, a fraction δ_{ij} is carried on, and when production takes place, an amount of τ is added. A disutility ϕ is incurred for a worker to choose an occupation different from his source one. It is used to capture the preparation cost when one seeks to switch occupation.

An off-job search worker faces the same decision problem as his on-the-job search counterpart. The difference is that, at this time, he has to apply even when he elects to be an occupational stayer, and he no longer has a safety net when his application fails (going back to work in the source occupation). In this sense, all occupations appear to be more homogeneous. When a worker searches off-job, he gets an offer with the occupation-specific job-finding rate. If he succeeds, he produces in the target occupation and then proceeds to the following separation stage; If he fails, he receives benefits and gets ready to search off-job in the following period. Again, a fixed mobility cost is incurred when one tries to switch occupation off-job (ϕ').

A worker in transition cannot search. He receives benefits from the government and waits to conduct off-job search in the period that follows. Please note that workers enter transition by displacement. Not to work is not a choice in the model. To concentrate on main issues, I assume that the government can perfectly monitor workers and announces that those who do not bother to apply are not eligible for the benefits. Because leisure is not valued and utility comes solely from consumption, no one will choose to be idle in this context.

I assume a log utility function in what follows.[18] This assumption helps simplify the model significantly. It can be shown that the constant $\log T$ shifts value functions in a parallel fashion and does not affect workers' optimal choice. So it can be removed from the model. Plugging the log wage

[18]Though not standard, some authors use concave utility functions in the studies of labor market, e.g. Shi (2009), Pavan (2011), Sullivan (2010) and Yamaguchi (2011). The last 3 assume a log utility function.

function in the wage regression into the value functions, one finds a set of variables as follows: a worker's race, rotation group number, education level, marital status, region, 1-digit industry, and whether being unionized. Among them, the first 2 are constants and hence can be removed safely. The remaining variables, especially education level[19] and marital status, tend not to change often and can be deemed as close constants. So I remove them as well. To compensate, an i.i.d. idiosyncratic shock ϵ is introduced. Apart from this, it is also used to capture the nonpecuniary factors that affect a worker's occupational choice decision, such as health, interest, and family commitment. More over, to make the model simple, instead of drawing ϵ's for all candidate occupations, it is drawn only for the source occupation. So, it actually reflects a difference effect: A very large positive number indicates that a worker really wants to stay in the current occupation; while a negative number with a large absolute value implies strong incentives to switch. The idiosyncratic shock is assumed to be normally distributed, with mean zero and standard deviation σ and σ' for on-the-job and off-job search workers, respectively.

So far the terms remain in Ω_t are General Occupational Tenure s_{it} and its coefficients. Recall that in Section 2 an aggregate shock is proposed. I denote it as χ_t here. The introduction of χ is to save me the effort of keeping track of the complex evolution of the coefficients on occupational returns. Further, I assume that ϵ is independent of χ.

The simplified value functions are listed as follows:

On-the-job search value function

$$V(i, s_{it}, \chi_t, \epsilon_t) = \max\{V_{stay}(i, s_{it}, \chi_t, \epsilon_t), V_{switch}(i, s_{it}, \chi_t, \epsilon_t)\} \tag{6}$$

where,

$$\begin{aligned}
&V_{stay}(i, s_{it}, \chi_t, \epsilon_t) = \\
&\quad \log(w_i(s_{it}, \chi_t)) + \beta(1 - q_{it})\mathbf{E}V(i, s_{it} + \tau, \chi_{t+1}, \epsilon_{t+1}) \\
&\quad + \beta q_{it}\mathbf{E}U(i, s_{it} + \tau, \chi_{t+1}, \epsilon_{t+1}) + \epsilon_t, \\
&V_{switch}(i, s_{it}, \chi_t, \epsilon_t) = \\
&\quad \max_{j \neq i, j \in I}\{p_{jt}[\log(w_j(s_{it}, \chi_t)) + \beta(1 - q_{jt})\mathbf{E}V(j, s_{it}\delta_{ij} + \tau, \chi_{t+1}, \epsilon_{t+1}) \\
&\quad + \beta q_{jt}\mathbf{E}U(j, s_{it}\delta_{ij} + \tau, \chi_{t+1}, \epsilon_{t+1})] \\
&\quad + (1 - p_{jt})[\log(w_i(s_{it}, \chi_t)) + \beta(1 - q_{it})\mathbf{E}V(i, s_{it} + \tau, \chi_{t+1}, \epsilon_{t+1}) \\
&\quad + \beta q_{it}\mathbf{E}U(i, s_{it} + \tau, \chi_{t+1}, \epsilon_{t+1})] - \phi\}
\end{aligned}$$

[19]The sample is selected such that workers have a stable attachment with the labor market. Basically, they have finished their education stage.

Off-job search value function

$$W(i, s_{it}, \chi_t, \epsilon_t) = \max\{W_{stay}(i, s_{it}, \chi_t, \epsilon_t), W_{switch}(i, s_{it}, \chi_t, \epsilon_t)\} \tag{7}$$

where,

$$\begin{aligned}
&W_{stay}(i, s_{it}, \chi_t, \epsilon_t) = \\
&\quad p'_{it}[\log(w_i(s_{it}, \chi_t)) + \beta(1 - q_{it})\mathbf{E}V(i, s_{it} + \tau, \chi_{t+1}, \epsilon_{t+1}) \\
&\quad + \beta q_{it}\mathbf{E}U(i, s_{it} + \tau, \chi_{t+1}, \epsilon_{t+1})] \\
&\quad + (1 - p'_{it})[\log(b) + \beta\mathbf{E}W(i, s_{it}, \chi_{t+1}, \epsilon_{t+1})] + \epsilon_t, \\
&W_{switch}(i, s_{it}, \chi_t, \epsilon_t) = \\
&\quad \max_{j \neq i, j \in I}\{p'_{jt}[\log(w_j(s_{it}, \chi_t)) + \beta(1 - q_{jt})\mathbf{E}V(j, s_{it}\delta_{ij} + \tau, \chi_{t+1}, \epsilon_{t+1}) \\
&\quad + \beta q_{jt}\mathbf{E}U(j, s_{it}\delta_{ij} + \tau, \chi_{t+1}, \epsilon_{t+1})] \\
&\quad + (1 - p'_{jt})[\log(b) + \beta\mathbf{E}W(i, s_{it}, \chi_{t+1}, \epsilon_{t+1})] - \phi'\}
\end{aligned}$$

Transition value function

$$U(i, s_{it}, \chi_t, \epsilon_t) = \log(b) + \beta\mathbf{E}W(i, s_{it}, \chi_{t+1}, \epsilon_{t+1}) \tag{8}$$

The aggregate shock χ_t takes on 2 values in the model: Good (g) or Bad (b). The value of g or b is determined with the help of Table 2. The average of intercept is calculated for each occupation and is used as a cutoff point. The periods in which the intercepts are above the cutoff point are called good times, otherwise bad times. This is done to all 5 occupations, and not surprisingly the conclusions are generally consistent, a pattern already shown by Table 3 and Figure 3. Then I calculate mean occupation-specific intercepts in good times β_{ig} and in bad times β_{ib}. I do the same for linear coefficient $\beta_{i\chi}^{OccTen}$ and quadratic coefficient $\beta_{i\chi}^{OccTenSq}$, $\chi \in \{g, b\}$. Based on the above parameters, the log wage in the value functions can be determined as follows:

$$\begin{aligned}
\log(w_i(s_i, \chi)) &= \beta_{i\chi} + \beta_{i\chi}^{OccTen} s_i + \beta_{i\chi}^{OccTenSq} s_i^2 \\
\log(w_j(s_i, \chi)) &= \beta_{j\chi} + \beta_{i\chi}^{OccTen} \delta_{ij} s_i + \beta_{i\chi}^{OccTenSq} (\delta_{ij} s_i)^2,
\end{aligned}$$

where $\chi \in \{g, b\}$.

Please note that the labor demand side (occupation side) is not explicitly modeled in the paper. Instead, I take an indirect approach: including the occupation-specific job-finding rates p_i's and p'_i's in the model. They are key equilibrium objects: In a general equilibrium model, both sides take them as given and make optimal decisions, and these decisions indeed generate the job-finding rates taken as given. In the current paper, they are obtained through calibration, and are functions of the aggregate shock.

5 Numerical Analysis

Like most discrete choice models, the model does not have an analytical solution and is solved numerically. In this section, I discuss how the model is parameterized and solved, and then analyze the results.

5.1 Direct Estimation

Recall that the model period is chosen the same as SIPP's reference time, 4 months or 1/3 year. Except otherwise stated, all the time variables in the paper are expressed in the units of years. In Section 2, the coefficients on occupation-specific returns are estimated through the wage regression. The intercept coefficient $\beta_{i\chi}$, linear coefficient $\beta_{i\chi}^{OccTen}$, and quadratic coefficient $\beta_{i\chi}^{OccTenSq}$ vary with occupations and aggregate economic conditions, where $i \in \{1, 2, 3, 4, 5\}, \chi \in \{g, b\}$. And they are evaluated according to the method presented in Section 4, on the basis of wage regression estimates.

Furthermore, the following parameters come from direct inference from data. The discount rate $\hat{\beta}$ is set to be 0.9870 to match an annual interest rate of 4%. The death probability ρ equals 0.007246 so that a worker's potential working life in the labor market is 46 years (aged 18–64). Jointly they imply that the value of effective discount rate β is 0.98. The per-period increment of General Occupational Tenure when one works in an occupation τ is equal to 1/3 (year). I choose b, the invariant benefits, to be 0.4629, so that the benefits are 36%[20] of the average wage rate in the economy (ignoring the linear and quadratic components of the returns). The aggregate shock χ is assumed to be i.i.d. and data show that it takes on g with the probability 0.625 and b 0.375.[21] The occupation-specific displacement rate is estimated by the displacement flow divided by its corresponding employment stock for each occupation. All the estimates in this subsection are summarized in Table 9.

[20]Kletzer and Rosen (2008) calculate the U.S. average replacement rate (average weekly benefits as a share of average weekly earnings) on the basis of Department of Labor data. The number is 0.36 for the years 1975 to 2004.

[21]In another version of the model, a Markov process is assumed. The paper's numerical results have hardly changed.

The table shows that the cross-sectional variation in the intercept component of occupational returns is similar under both aggregate shocks, and so is the order of magnitudes, from big to small: Professional, Craft, Technical, Operators, and Service. A negative shock brings the intercept return slightly down in all 5 occupations with the average decine of 4.09%. The cross-occupational difference of the less important return parts, linear and quadratic, also does not see an obvious variation in good times than in bad times, and a bad shock causes the linear return coefficients uniformly higher (except going down in Professional) and the quadratic ones uniformly lower (except both zero in Professional). For occupation-specific displacement rates, the cross-sectional variation has little changes across aggregate economic conditions, but a negative shock's impact is very different among distinctive occupations: The displacement rates in Technical, Craft, and Operators are relatively stable, while Professional experiences an 18.16% increase and Service an even sharper one, 47.03%.

As a reminder, the Transfer Matrix, which is needed when I discount the General Occupational Tenure for switchers, can be found in Table 1.

5.2 Calibration Strategy

The parameters cannot be evaluated in the above process include: the occupation-specific job-finding rates $p_{i\chi}$'s (on-the-job) and $p'_{i\chi}$'s (off-job), where $i \in \{1, 2, 3, 4, 5\}, \chi \in \{g, b\}$; fixed mobility costs ϕ (on-the-job) and ϕ' (off-job); and the standard deviations of idiosyncratic shocks σ (on-the-job) and σ' (off-job).[22] To keep the model tightly parameterized, I assume $p'_{i\chi} = \gamma p_{i\chi}, \gamma \in (0, 1)$. That is, the job-finding rates for off-job search workers are uniformly lower than their counterparts for on-the-job search workers, by a constant factor γ. To summarize, there are 15 values to be determined in total: $p_{i\chi}$'s where $i \in \{1, 2, 3, 4, 5\}, \chi \in \{g, b\}$, γ, ϕ, ϕ', σ and σ'. I denote the set of unknown parameters Θ and evaluate Θ through calibration.

In particular, I calibrate the model to match the starred flows in Tables 4 to 7, or mobility distributions. The calibration consists of 2 steps. In the first step, given a set of values for the 15 parameters, the model is solved numerically. It is easy to show that the model can be expressed as a system of 2 nested functional equations: on-the-job search value function V and off-job search value function W. Using value function iteration, one function can be solved given another function. Therefore, I keep performing value function iterations for V and W alternately until the system converges. In

[22]The means of idiosyncratic shocks are assumed to be zero for workers of both search types.

Step 2, I simulate the model to get the statistics corresponding to the starred ones in Tables 4 to 7, and compute the sum of squared differences between the 2 sets of statistics based on the data and on the model. The whole process is repeated until the difference is minimized by the simplex method and the resultant Θ are the values desired. The algorithm is demonstrated in Figure 7.

5.3 Calibration Results

Table 10 lists the calibration results. As shown in the table, the job-finding rates for on-the-job search workers differ across occupations, varying from 30.99% (Professional) to 53.36% (Service) in good times and from 27.40% (Technical) to 32.85% (Craft) in bad times: The cross-sectional difference is bigger under good shocks than under bad shocks. A negative aggregate shock makes the job-finding rate significantly lower for all occupations except Professional: The Professional job-finding rate declines by 8.29%, whereas the average decrease for the other 4 occupations is 35.54%. As a consequence of the drop, the mean transition duration goes up in all occupations, a feature can be found in Table 8. The job-finding rates for off-job search workers are about 80% of the corresponding rates for on-the-job search workers: The gap is moderate.

The fixed mobility cost for an on-the-job switch is 4.92, roughly equivalent to 21.3 hours of hourly wage for an average worker with 30 years of General Occupational Tenure; whereas the cost for an off-job switch is 2.34, only about 1.6 hours of hourly wage for a same average worker. The reason for a higher on-the-job mobility cost might be that preparing for a new career while holding a full-time job is more challenging than with no job at hand, both phisically and intellectually, and thus incurs higher disutility. The standard deviation of the idiosyncratic shock for an employed worker is 8.65, which is around 4.74% of the average lifetime utility for an employed worker with 30 years of General Occupational Tenure, while for a worker in transition, the shock's standard deviation is higher at the level of 11.33, or roughly 6.19% of the average lifetime utility for a worker in transition with 30 years of General Occupational Tenure. It's not very clear why an off-job search worker has a stronger intentive to leave or to stay in his source occupation than an on-the-job search worker does, and maybe it is related with some psychological issues.

5.4 Model Fit

To evaluate the model's performance, I do 2 checks. The first check is to see how much the model can account for the 2 sets of distributions, occupational mobility (Tables 4 to 7) and transition time (Figure 6). The simulations are conducted to generate both distributions. The mobility distributions based on model simulation are presented in Tables 4 to 7 with numbers in parentheses. And the transition time distributions from model simulation are displayed graphically as Part (b) in Figure 6, from which the mean transition time is computed for each occupation and demonstrated in parentheses in Table 8. In comparing model-based and data-based distributions, I can tell what fraction of the data distributions can be accounted for by the model. Specifically, if a mass probability in the data distributions takes on a value x, and its corresponding value in the model distributions is y, and then $y/x \times 100\%$ is the fraction accounted for. In many cases, y is no more than x and this ratio is less than or equal to 100%. Under circumstances where $y > x$, the formula $(1-y)/(1-x) \times 100\%$ is used: x is over accounted for because its complement, $1 - x$[23], is under accounted for. It turns out that the model can account for 65.46% of the mobility distributions and 76.30% of the transition time distributions. Note that the former are targeted when the model is calibrated, but in no time do I try to match the latter. In this sense, the model does a good job.

Secondly, I examine the 4 occupational mobility facts discussed in Section 3 one by one. As for Fact 1, the model successfully generates the occupational choice persistence. As shown by the parenthesized numbers in Tables 4 to 7, generally more than 70% of workers work in their source occupation. But it also has a limitation: the on-the-job search persistence seems not significantly stronger than that in the off-job search as in data, due to the fact that the model largely underestimates the persistence for employed workers in all occupations. The model does not work well in reproducing Fact 2, that the tendency to switch occupation declines as workers accumulate the General Occupational Tenure. As can be seen in Tables 4 and 5, the model generates too high stayer fractions for low-skill subgroups and too low stayer fractions for medium- and high-skill subgroups. The model fits Fact 3 fairly well in that it accurately predicts the major occupational targets for occupational switchers in 3 occupations, Professional, Craft, and Operators, but the outflow directions for source occupations Technical and Service are missed. As far as Fact 4, the ordering of occupation-specific

[23] All numbers in the distributions are percentage points and no more than 1. When $y > x$, x is necessarily less than 1.

mean transition times is concerned, the model's performance is satisfactory. The order it generates is: Professional, Technical, Craft, Operators, and Service, which are listed in Table 8. Except Service, the other 4 occupations are put in the right place. However, one problem is that the model underreports the length of average transition period for all occupations. An investigation of Figure 6 reveals the reason: The model-based fraction of workers who spend medium transition times is too high in each occupation, while that of workers experiencing long transition durations is too low.

Despite the limitations discussed above, the model is reasonable. In general, it captures the main features found in the data, especially given its highly parsimonious nature. Empirical occupational choice models often have a large set of parameters to estimate. For instance, Keane and Wolpin (1997) has more than 80 parameters to pin down, and Sullivan (2010) estimates nearly 200 model variables. In this paper, only 15 parameter values are obtained through solving the model. More importantly, the purpose of this paper is to find out which shock, aggregate or idiosyncratic, is more important in understanding the occupational mobility, and what factors may act to obstruct the mobility. With only a small number of key variables in the model, it is relatively easy to identify the role each factor plays and to arrive fast at the answer.

5.5 Experiments

With the structural model at hand, I do 2 numerical experiments to answer the questions raised at the very beginning in the paper. The first question is: How important are idiosyncratic versus aggregate shocks in understanding the occupational mobility? To address this question, I start with the benchmark model, and first take away idiosyncratic shocks to see how the modified model can account for the mobility and transition duration distributions, and then do a similar exercise by removing only aggregate shocks to see what happens. Recall that aggregate shocks affect the following occupation-specific variables: job-finding rates, displacement rates, intercept, linear, and quadratic returns. By removing aggregate shocks, I mean letting each of these variables take on the value of its average across aggregate shocks. Table 11 lists the exercise's results. It shows the fraction of occupational mobility distributions that can be accounted for under each circumstance.[24] As already known, with both shocks present the benchmark model can account for 65.46% of the mobility distributions. However, re-

[24]Subsection 5.4 discusses the method on how I calculate the fraction of a data-based distribution accounted for by the model.

moving the idiosyncratic shock makes the fraction drop sharply to 10.91%. In contrast, with the absence of aggregate shocks, the fraction accounted for sees almost no change (65.45%).[25]

As a demonstration, Figure 8 compares the policy function for the off-job search Craft workers at bad times under 2 scenarios: with and without idiosyncratic shocks. Panel (a) of the figure shows the workers' best occupational choice when there exist idiosyncratic shocks. In solving the benchmark model, I discretize the idiosyncratic shock ϵ into 5 values, $\epsilon 1 < \epsilon 2 < \epsilon 3 < \epsilon 4 < \epsilon 5$ with $\epsilon 3 = 0$, $\epsilon 1, \epsilon 2$ negative and $\epsilon 4, \epsilon 5$ positive. Recall that a very negative value indicates strong incentives to switch occupation while a very positive one to stay. In Panel (a), if a worker is hit by $\epsilon 1$ or $\epsilon 2$, his optimal target is Occupation 1 (Professional) when his General Occupational Tenure is less than 5 years and Occupation 5 (Operators, an occupation closer to Craft than Professional) when he has more than 5 years of General Occupational Tenure. However, if he is hit by other shocks, he will choose to stay in Craft (Occupation 4). As opposed to Panel (a), Panel (b) depicts the worker's best choice when there is no idiosyncratic shock. His policy function is quite simple in this case: never to switch regardless of his skill level, as if he were always hit by $\epsilon 3$ in the world of idiosyncratic shocks. As Figure 8 shows, when the idiosyncratic shock is taken away from the model, there will be too little mobility generated, and hence the explained fraction of mobility distributions drops dramatically.

The first experiment shows that it is idiosyncratic shocks, or more accurately, the very negative realizations of idiosyncratic shocks that induce workers to switch occupation. A following question naturally is: What are the barriers to the occupational mobility. In Experiment 2, I examine 3 factors, fixed mobility costs, search frictions, and the transfer loss of General Occupational Tenure to assess their quantitative importances in this respect. The experiment is conducted in the same spirit as in Experiment 1. Once again, I start with the benchmark model, and deviate from it by first taking away fixed mobility costs, then search frictions, finally the transfer loss, one factor at a time, to see how the model performs. The experiment results are displayed in Table 12.

To remove fixed mobility costs, I let both ϕ and ϕ' equal zero. As Table 12 shows, if the fixed mobility costs are taken away, there is a moderate decrease in the explained fraction of the mobility distributions from 65.5% to 49.6%, while the explained fraction of the transition time distributions

[25] Because neither of the modifications brings noticeable change to the fraction of transition time distributions the model can account for, the result reports are omitted.

keeps essentially unchanged. Figure 9 further illustrates that, the removal of mobility costs results in an excess of occupational mobility. It compares the policy function for the on-the-job search Operators at good times under 2 scenarios: with and without the fixed mobility cost, in a similar manner as in Figure 8. Consider workers who face a zero value of the idiosyncratic shock. With the presence of the mobility cost, an operator's best choice is to stay as shown in Panel (a). In contrast, if the mobility cost is eliminated, workers can afford to switch to Occupation 4 (Craft) when they have a General Occupational Tenure less than 15 years or greater than 30 years, as depicted in Panel (b). So taking fixed mobility costs away will cause the model to generate too much mobility, opposite to the case of the removal of idiosyncratic shocks, but both of them will make the explained fraction of mobility distributions decline.

Next, I make all the job-finding rates equal one for both on-the-job and off-job search workers, that is, $p_{i\chi} = 1, \gamma = 1, i \in \{1, 2, 3, 4, 5\}, \chi \in \{g, b\}$, to eliminate search frictions. As opposed to the fixed mobility costs, search frictions' impact is mainly on the transition time distributions. Without search frictions, the fraction of duration distributions the model can account for simply drops to zero, or there is no transition at all.[26] This result is no surprise since search frictions are the unique mechanism that generates transition in the model. Search frictions, however, does not seem to have obvious effects on mobility distributions: elimination of them leads to almost no change in the fraction of mobility distributions the model can account for.

To make all the occupational switches without a loss of General Occupational Tenure, I let all the elements in the Transfer Matrix equal one, namely, $\delta_{ij} = 1, i, j \in \{1, 2, 3, 4, 5\}$. Like fixed mobility costs, the transfer loss of General Occupational Tenure basically sees its influence on the mobility distributions. If it is taken away, there is a modest decline in the explained fraction of mobility distributions from 65.6% to 60.9%, and no apparent change in the explained fraction of transition time distributions. Figure 10 demonstrates the role that transfer loss plays in obstructing the occupational mobility. To focus on main issues, suppose there are neither mobility costs nor search frictions in the economy. Moreover, also assume there is no aggregate shock or exogenous separation. The figure plots the log wage as a function of the General Occupational Tenure for 2 occupations,

[26] Strictly speaking, all separated workers experience one period of transition. Because the model assumes that a worker cannot search immediately after being displaced and has to wait for one period.

Technical and Operators. Consider an operator with 30 years of General Occupational Tenure. His current log wage is 1.77 at Point A. If he thinks of switching to Technical, without a transfer loss he will carry 100% or 30 years of General Occupational Tenure to the new occupation and receive a log wage of 1.82, which is represented by Point B. However, in case the transfer loss exists, he can transfer only 16% or 4.8 years of General Occupational Tenure to Technical, according to the Transfer Matrix, and thus earn a log wage of 1.58, indicated by Point C. Hence he will give up the idea of switching. It's obvious that the transfer loss constitutes a barrier to the occupational mobility. But in the model it is less important than the fixed mobility costs in a quantitave sense.

6 Conclusions

In this paper, I document 4 facts on the occupational mobility, making use of SIPP's unique interview structure. Motivated by the facts, a directed search model is built to investigate the mechanism of aggregate mobility across occupations and labor market statuses. The model includes both aggregate and idiosyncratic shocks, and contains occupational human capital measured by the General Occupational Tenure as well as search frictions. The model can account for 65% of the occupational mobility distributions and 76% of the transition time distributions found in the data. And it also captures the main features of the 4 emphasized facts. To examine what role each factor plays in generating the mobility, I conduct 2 numerical experiments. Using the model, I show that idiosyncratic shocks are the main determinant of occupational mobility whereas aggregate shocks are unimportant, and that fixed mobility costs and search frictions constitute significant barriers to the mobility while the transfer loss of General Occupational Tenure is only of modest importance quantitatively.

In the model, the aggregate shock affects an array of occupation-specific variables: job-finding rates (for employed workers and workers in transition); displacement rate; intercept, linear, and quadratic occupational returns. Some of them are estimated directly from data, and others are obtained from model calibration. As shown in the paper, a negative shock generally lowers job-finding rates, raises displacement rate, and makes the intercept and quadratic returns go down while the linear component go up, in each occupation. But it is hard to figure out how the aggregate shock exerts its influence on those occupation-specific variables in a partial-equilibrium model. Indeed, they are equilibrium objects in an economy (especially the job-finding rates and return components). To study the process of how the variables achieve their equilibrium levels given an aggregate shock, a general-equilibrium model is needed.

Another issue deserves further investigations is the nature of idiosyncratic shocks, which are the main determinant of occupational mobility. It is found in the paper that the shock's variance is larger for workers in transition than for workers employed, but the reason remains unclear. One conjecture is that a worker's individual shock is correlated with his transition duration. The model abstracts from private savings and does not track workers' benefits collection history. It assumes that a worker in transition can receive social benefits infinitely. But of course in reality, there is a time limit. This might be a direction to pursue further studies.

References

Gathmann, C. and U. Schonberg (2010), "How general is human capital? a task-based approach." *Journal of Labor Economics*, 28, 1–49.

Hoffmann, F (2010), "An empirical model of life-cycle earnings and mobility dynamics." *Mimeo, University of British Columbia*.

Kambourov, G. and I. Manovskii (2009), "Occupational mobility and wage inequality." *Review of Economic Studies*, 76, 731–759.

Keane, M.P. and K.I. Wolpin (1997), "The career decisions of young men." *Journal of Political Economy*, 105, 473–522.

Kletzer, L.G. and H. Rosen (2008), "Reforming unemployment insurance for the twenty-first-century workforce." *Path to prosperity: Hamilton Project ideas on income security, education, and taxes*, 63.

Lucas, R.E. and E.C. Prescott (1974), "Equilibrium search and unemployment." *Journal of Economic Theory*, 7, 188–209.

Menzio, G. and S. Shi (2011), "Efficient search on the job and the business cycle." *Journal of Political Economy*, 119, 468–510.

Moen, E.R. (1997), "Competitive search equilibrium." *Journal of Political Economy*, 105, 385–411.

Pavan, R. (2011), "Career choice and wage growth." *Journal of Labor Economics*, 29, 549–587.

Shi, S. (2009), “Directed search for equilibrium wage–tenure contracts.” *Econometrica*, 77, 561–584.

Sullivan, P. (2010), “A dynamic analysis of educational attainment, occupational choices, and job search.” *International Economic Review*, 51, 289–317.

Yamaguchi, S. (2011), “Tasks and heterogeneous human capital.” *Mimeo, McMaster University.*

Table 1: Distance/Transfer Rate For Occupation Pairs

Source	Target				
	1	2	3	4	5
1	0/1	0.10/0.72	0.39/0.24	0.53/0.13	0.58/0.10
2	0.10/0.72	0/1	0.30/0.35	0.44/0.20	0.48/0.16
3	0.39/0.24	0.30/0.35	0/1	0.17/0.56	0.24/0.44
4	0.53/0.13	0.44/0.20	0.17/0.56	0/1	0.07/0.80
5	0.58/0.10	0.48/0.16	0.24/0.44	0.07/0.80	0/1

NOTES: In each cell, there are 2 numbers. The left one refers to the distance between the source and target occupations and is in the units of radians. The right one is the Transfer Rate for the pair. Occupations 1 to 5 correspond to Professional, Technical, Service, Craft, and Operators, respectively.

Table 2: Results of Wage Regression

	Wave2	Wave3	Wave4	Wave5	Wave6	Wave7	Wave8	Wave9
EmpTen	-0.1090*	-0.0296	-0.0628	-0.0582	-0.0669	-0.0260	-0.1420**	-0.0749
EmpTenSq	-0.000057	-0.000302	-0.000215	-0.000370	-0.000333	0.000529	0.000305	-0.000744
WorkExp	0.0886	0.1920***	0.1060	0.0595	0.0872	0.0592	0.1210*	0.0795
WorkExpSq	-0.000170	-0.000189	-0.000165	-0.000331	-0.000328	-0.000104	-0.000343	0.000133
IndTen	0.0365	-0.1220	-0.0102	0.0282	0.0229	0.0036	0.0659	0.0208
IndTenSq	-0.000346	-0.000398	-0.000102	0.000213	0.000252	-0.000739	-0.000905	-0.000285
Edu	0.0184	0.0127	0.0132	0.0184	0.0270*	0.0305**	0.0245*	0.0231
EduSq	0.001100	0.001270	0.001140	0.000900	0.000611	0.000453	0.000671	0.000675
I1	1.604***	1.677***	1.609***	1.579***	1.599***	1.648***	1.671***	1.665***
I2	1.385***	1.505***	1.471***	1.423***	1.457***	1.510***	1.539***	1.517***
I3	1.307***	1.403***	1.335***	1.281***	1.309***	1.332***	1.367***	1.333***
I4	1.443***	1.577***	1.572***	1.523***	1.528***	1.526***	1.532***	1.520***
I5	1.372***	1.501***	1.479***	1.439***	1.444***	1.455***	1.485***	1.463***
I1_OccTen	0.0190	0.0247*	0.0284**	0.0230**	0.0211*	0.0179*	0.0180*	0.0176*
I2_OccTen	0.0271***	0.0257***	0.0289***	0.0304***	0.0255***	0.0182***	0.0149**	0.0143**
I3_OccTen	0.0218**	0.0222***	0.0299***	0.0308***	0.0263***	0.0225***	0.0207***	0.0228***
I4_OccTen	0.0341***	0.0305***	0.0287***	0.0283***	0.0279***	0.0288***	0.0289***	0.0270***
I5_OccTen	0.0224***	0.0191***	0.0191***	0.0181***	0.0193***	0.0188***	0.0161***	0.0164***
I1_OccTenSq	-0.000265	-0.000455	-0.000482	-0.000283	-0.000240	-0.000202	-0.000261	-0.000302
I2_OccTenSq	-0.000452**	-0.000435**	-0.000540***	-0.000613***	-0.000469**	-0.000266	-0.000182	-0.000167
I3_OccTenSq	-0.000434	-0.000455*	-0.000734***	-0.000785***	-0.000631**	-0.000519**	-0.000524*	-0.000598**
I4_OccTenSq	-0.000666***	-0.000589***	-0.000557***	-0.000557***	-0.000549***	-0.000589***	-0.000599***	-0.000561***
I5_OccTenSq	-0.000320**	-0.000259*	-0.000270**	-0.000255*	-0.000283**	-0.000276**	-0.000222*	-0.000262**
Obs	8813	9037	9177	9268	9364	9441	9423	9407

NOTES: Each column stands for an independent regression, with the title indicating what data are used. For instance, Wave 2 implies that the particular regression is based on data starting from Wave 2, namely, data from Waves 2, 3, and 4. The numbers in the table are estimated coefficients on the regressors, which are listed in the first column. The stars next to an estimate indicate its significance level, with single star implying 5%, double star 1%, and triple star 0.1%. Number of observations is on the last row.

Table 3: Coefficient of Correlation for Pairwise Intercept Returns

Occupation	Occupation				
	1	2	3	4	5
1	1	...	...	...	...
2	0.8460	1	...	...	...
3	0.8642	0.7014	1	...	...
4	0.3405	0.6063	0.5667	1	...
5	0.6176	0.8332	0.7212	0.9301	1

NOTES: Occupations 1 to 5 correspond to Professional, Technical, Service, Craft, and Operators, respectively.

Table 4: Occupational Mobility Distributions for Off-Job Search Workers in Good Time

Source	Target														
	GenOccTen ≤ 14					$14 <$ GenOccTen ≤ 28					GenOccTen > 28				
1	1**	2*	3	4	5	1**	2	3	4	5	1**	2	3	4	5
	68.57	15.19	6.47	3.70	6.08	89.74	8.41	0	1.85	0	100	0	0	0	0
	(84.62)	(9.23)	(0)	(6.15)	(0)	(72.73)	(27.27)	(0)	(0)	(0)	(58.33)	(41.67)	(0)	(0)	(0)
2	2**	1	3	4*	5*	2**	1	3	4	5	2**	1	3	4	5
	60.72	5.24	7.76	12.71	13.56	85.79	4.53	0	5.28	4.40	84.11	8.66	0	7.23	0
	(83.67)	(16.33)	(0)	(0)	(0)	(79.07)	(20.93)	(0)	(0)	(0)	(91.67)	(8.33)	(0)	(0)	(0)
3	3**	4	5*	2	1	3**	4	5	2	1	3**	4	5	2	1
	66.95	7.19	19.89	4.50	1.47	85.26	3.10	5.48	2.67	3.49	100	0	0	0	0
	(76.74)	(21.71)	(0)	(0)	(1.55)	(91.18)	(8.82)	(0)	(0)	(0)	(83.33)	(16.67)	(0)	(0)	(0)
4	4**	5*	3	2	1	4**	5*	3	2	1	4**	5	3	2	1
	73.26	18.39	0	6.13	2.22	79.20	10.46	1.65	4.45	4.23	96.50	0	3.50	0	0
	(78.80)	(8.29)	(0)	(0)	(12.90)	(72.53)	(27.47)	(0)	(0)	(0)	(82.14)	(17.86)	(0)	(0)	(0)
5	5**	4*	3	2*	1	5**	4	3	2	1	5**	4	3	2	1
	69.12	13.70	5.17	9.98	2.04	89.03	8.40	2.57	0	0	83.91	6.90	9.19	0	0
	(74.53)	(18.24)	(0)	(0)	(7.23)	(80.26)	(19.74)	(0)	(0)	(0)	(86.96)	(13.04)	(0)	(0)	(0)

NOTES: The table is divided into 2 parts, with the left part Source and the right part Target, implying that a worker used to be working in occupation Source before time $t-1$ and works in occupation Target at time t. GenOccTen refers to the General Occupational Tenure. The table's right part consists of 3 groups of data according to the skill level: low, medium, and high, depending on the length of GenOccTen which is in the units of years. The 5 columns under each skill level represent the 5 occupations worked at time t. Depending on their distances from the source occupation, the 5 occupations are listed in the order from near to far, with the leftmost column closest to the source occupation and the rightmost farthest. Given a source occupation, all workers of the same skill level constitute a subgroup. The numbers are the flow percentages for a given subgroup. Numbers without parentheses are from data and those in parentheses from model simulation. For numbers coming from data, those no less than 10% are marked with single stars and 50% double stars. Occupations 1 to 5 correspond to Professional, Technical, Service, Craft, and Operators, respectively.

Table 5: Occupational Mobility Distributions for Off-Job Search Workers in Bad Time

Source	Target														
	GenOccTen $\leq$ 14					14 $<$ GenOccTen $\leq$ 28					GenOccTen $>$ 28				
1	1**	2*	3	4	5*	1**	2	3	4	5	1**	2	3	4	5
	58.02	20.98	2.67	6.64	11.69	92.92	7.08	0	0	0	100	0	0	0	0
	(71.43)	(28.57)	(0)	(0)	(0)	(76.92)	(23.08)	(0)	(0)	(0)	(33.33)	(66.67)	(0)	(0)	(0)
2	2**	1	3	4*	5*	2**	1	3	4	5*	2**	1	3	4	5*
	56.07	6.83	1.36	15.25	20.48	74.11	6.52	2.47	6.20	10.70	81.22	0	0	0	18.78
	(73.42)	(26.58)	(0)	(0)	(0)	(82.76)	(17.24)	(0)	(0)	(0)	(80.00)	(20.00)	(0)	(0)	(0)
3	3**	4*	5*	2	1	3**	4	5	2	1	3**	4	5	2	1
	67.55	13.02	10.38	9.06	0	95.75	0	0	4.25	0	100	0	0	0	0
	(82.14)	(17.86)	(0)	(0)	(0)	(55.56)	(44.44)	(0)	(0)	(0)	(100)	(0)	(0)	(0)	(0)
4	4**	5*	3	2	1	4**	5	3	2	1	4**	5	3	2	1
	73.85	19.03	1.83	3.93	1.36	93.49	2.29	0	2.20	2.01	91.39	2.53	3.84	2.24	0
	(70.53)	(18.95)	(0)	(0)	(10.53)	(68.63)	(31.37)	(0)	(0)	(0)	(67.86)	(32.14)	(0)	(0)	(0)
5	5**	4*	3	2	1	5**	4	3	2	1	5**	4	3	2	1
	70.41	14.72	2.59	8.71	3.57	88.03	6.52	0	2.78	2.66	100	0	0	0	0
	(81.76)	(13.21)	(0)	(0)	(5.03)	(80.39)	(19.61)	(0)	(0)	(0)	(100)	(0)	(0)	(0)	(0)

NOTES: The table is divided into 2 parts, with the left part Source and the right part Target, implying that a worker used to be working in occupation Source before time $t-1$ and works in occupation Target at time t. GenOccTen refers to the General Occupational Tenure. The table's right part consists of 3 groups of data according to the skill level: low, medium, and high, depending on the length of GenOccTen which is in the units of years. The 5 columns under each skill level represent the 5 occupations worked at time t. Depending on their distances from the source occupation, the 5 occupations are listed in the order from near to far, with the leftmost column closest to the source occupation and the rightmost farthest. Given a source occupation, all workers of the same skill level constitute a subgroup. The numbers are the flow percentages for a given subgroup. Numbers without parentheses are from data and those in parentheses from model simulation. For numbers coming from data, those no less than 10% are marked with single stars and 50% double stars. Occupations 1 to 5 correspond to Professional, Technical, Service, Craft, and Operators, respectively.

Table 6: Occupational Mobility Distributions for On-The-Job Search Workers in Good Time

Source	Result														
	GenOccTen ≤ 14					$14 <$ GenOccTen ≤ 28					GenOccTen > 28				
1	1**	2	3	4	5	1**	2	3	4	5	1**	2	3	4	5
	98.86	0.15	0.22	0.61	0.16	99.47	0	0	0	0.53	100	0	0	0	0
	(79.25)	(18.14)	(0)	(2.61)	(0)	(75.00)	(25.00)	(0)	(0)	(0)	(84.71)	(15.29)	(0)	(0)	(0)
2	2**	1	3	4	5	2**	1	3	4	5	2**	1	3	4	5
	99.08	0.07	0.21	0.22	0.42	99.84	0	0	0	0.16	100	0	0	0	0
	(77.18)	(22.82)	(0)	(0)	(0)	(77.36)	(22.64)	(0)	(0)	(0)	(73.48)	(26.52)	(0)	(0)	(0)
3	3**	4	5	2	1	3**	4	5	2	1	3**	4	5	2	1
	99.52	0.08	0.20	0.20	0	100	0	0	0	0	100	0	0	0	0
	(77.86)	(22.14)	(0)	(0)	(0)	(76.66)	(23.34)	(0)	(0)	(0)	(79.49)	(20.51)	(0)	(0)	(0)
4	4**	5	3	2	1	4**	5	3	2	1	4**	5	3	2	1
	99.48	0.45	0	0	0.07	99.77	0.14	0.03	0	0.05	99.89	0.11	0	0	0
	(76.88)	(15.24)	(0)	(0)	(7.88)	(76.16)	(23.84)	(0)	(0)	(0)	(77.42)	(22.58)	(0)	(0)	(0)
5	5**	4	3	2	1	5**	4	3	2	1	5**	4	3	2	1
	99.49	0.24	0.13	0.12	0.03	99.79	0	0.06	0.15	0	100	0	0	0	0
	(77.55)	(22.45)	(0)	(0)	(0)	(76.63)	(23.37)	(0)	(0)	(0)	(74.75)	(25.25)	(0)	(0)	(0)

NOTES: The table is divided into 2 parts, with the left part Source and the right part Result, implying that a worker works in occupation Source at time $t-1$ and in occupation Result at time t. GenOccTen refers to the General Occupational Tenure. The table's right part consists of 3 groups of data according to the skill level: low, medium, and high, depending on the length of GenOccTen which is in the units of years. The 5 columns under each skill level represent the 5 occupations worked at time t. Depending on their distances from the source occupation, the 5 occupations are listed in the order from near to far, with the leftmost column closest to the source occupation and the rightmost farthest. Given a source occupation, all workers of the same skill level constitute a subgroup. The numbers are the flow percentages for a given subgroup. Numbers without parentheses are from data and those in parentheses from model simulation. For numbers coming from data, those no less than 10% are marked with single stars and 50% double stars. Occupations 1 to 5 correspond to Professional, Technical, Service, Craft, and Operators, respectively.

Table 7: Occupational Mobility Distributions for On-The-Job Search Workers in Bad Time

Source	Result														
	GenOccTen ≤ 14					$14 <$ GenOccTen ≤ 28					GenOccTen > 28				
1	1**	2	3	4	5	1**	2	3	4	5	1**	2	3	4	5
	99.80	0	0	0.20	0	100	0	0	0	0	100	0	0	0	0
	(77.73)	(20.34)	(0)	(1.93)	(0)	(83.14)	(16.86)	(0)	(0)	(0)	(78.72)	(21.28)	(0)	(0)	(0)
2	2**	1	3	4	5	2**	1	3	4	5	2**	1	3	4	5
	99.72	0	0	0.10	0.18	100	0	0	0	0	100	0	0	0	0
	(74.48)	(25.52)	(0)	(0)	(0)	(78.82)	(21.18)	(0)	(0)	(0)	(77.11)	(22.89)	(0)	(0)	(0)
3	3**	4	5	2	1	3**	4	5	2	1	3**	4	5	2	1
	99.06	0.14	0.18	0.39	0.24	100	0	0	0	0	100	0	0	0	0
	(77.06)	(22.94)	(0)	(0)	(0)	(81.95)	(18.05)	(0)	(0)	(0)	(63.64)	(36.36)	(0)	(0)	(0)
4	4**	5	3	2	1	4**	5	3	2	1	4**	5	3	2	1
	99.52	0.28	0.13	0.06	0	99.94	0.06	0	0	0	100	0	0	0	0
	(78.85)	(15.89)	(0)	(0)	(5.26)	(77.17)	(22.83)	(0)	(0)	(0)	(76.35)	(23.65)	(0)	(0)	(0)
5	5**	4	3	2	1	5**	4	3	2	1	5**	4	3	2	1
	99.54	0.23	0.16	0.07	0	100	0	0	0	0	100	0	0	0	0
	(77.78)	(21.64)	(0)	(0)	(0.58)	(78.40)	(21.60)	(0)	(0)	(0)	(76.86)	(23.14)	(0)	(0)	(0)

NOTES: The table is divided into 2 parts, with the left part Source and the right part Result, implying that a worker works in occupation Source at time $t-1$ and in occupation Result at time t. GenOccTen refers to the General Occupational Tenure. The table's right part consists of 3 groups of data according to the skill level: low, medium, and high, depending on the length of GenOccTen which is in the units of years. The 5 columns under each skill level represent the 5 occupations worked at time t. Depending on their distances from the source occupation, the 5 occupations are listed in the order from near to far, with the leftmost column closest to the source occupation and the rightmost farthest. Given a source occupation, all workers of the same skill level constitute a subgroup. The numbers are the flow percentages for a given subgroup. Numbers without parentheses are from data and those in parentheses from model simulation. For numbers coming from data, those no less than 10% are marked with single stars and 50% double stars. Occupations 1 to 5 correspond to Professional, Technical, Service, Craft, and Operators, respectively.

Table 8: Mean Transition Time for All Source Occupations

Source	Good Time	Bad Time
1	4.11(3.09)	5.28(3.47)
	16.44(12.36)	21.12(13.88)
2	3.97(2.85)	4.58(3.07)
	15.88(11.40)	18.32(12.28)
3	3.56(2.54)	4.22(2.59)
	14.24(10.16)	16.88(10.36)
4	3.22(2.68)	4.07(2.93)
	12.88(10.72)	16.28(11.72)
5	3.14(2.66)	4.00(2.91)
	12.56(10.64)	16.00(11.64)

NOTES: For each source occupation, numbers on the top row are in the units of waves, the reference period of SIPP interview, where one wave equals 4 months; numbers on the bottom row are the equivalent mean transition times in the units of months, calculated from the top row numbers. Numbers without parentheses are based on the data, while numbers in parentheses are from model simulation. Occupations 1 to 5 correspond to Professional, Technical, Service, Craft, and Operators, respectively.

Table 9: Parameters Obtained Not Through Calibration

Occupation-specific Returns			
β_{1g}	1.654	β_{1b}	1.594
β_{2g}	1.508	β_{2b}	1.422
β_{3g}	1.354	β_{3b}	1.299
β_{4g}	1.545	β_{4b}	1.498
β_{5g}	1.477	β_{5b}	1.418
β_{1g}^{OccTen}	0.0213	β_{1b}^{OccTen}	0.0210
β_{2g}^{OccTen}	0.0204	β_{2b}^{OccTen}	0.0277
β_{3g}^{OccTen}	0.0236	β_{3b}^{OccTen}	0.0263
β_{4g}^{OccTen}	0.0288	β_{4b}^{OccTen}	0.0301
β_{5g}^{OccTen}	0.0179	β_{5b}^{OccTen}	0.0199
$\beta_{1g}^{OccTenSq}$	0	$\beta_{1b}^{OccTenSq}$	0
$\beta_{2g}^{OccTenSq}$	-0.000318	$\beta_{2b}^{OccTenSq}$	-0.000511
$\beta_{3g}^{OccTenSq}$	-0.000566	$\beta_{3b}^{OccTenSq}$	-0.000617
$\beta_{4g}^{OccTenSq}$	-0.000579	$\beta_{4b}^{OccTenSq}$	-0.000591
$\beta_{5g}^{OccTenSq}$	-0.000258	$\beta_{5b}^{OccTenSq}$	-0.000286
General Parameters			
$\hat{\beta}$	0.9870	ρ	0.007246
τ	0.3333	b	0.4629
Aggregate Shock Probabilities			
P_g	0.625	P_b	0.375
Occupation-specific Displacement Rates			
q_{1g}	0.1586	q_{1b}	0.1874
q_{2g}	0.1318	q_{2b}	0.1286
q_{3g}	0.1163	q_{3b}	0.1710
q_{4g}	0.0914	q_{4b}	0.0860
q_{5g}	0.0891	q_{5b}	0.0904

NOTES: Occupations 1 to 5 correspond to Professional, Technical, Service, Craft, and Operators, respectively. Both $\beta_{1g}^{OccTenSq}$ and $\beta_{1b}^{OccTenSq}$ equal zero because the coefficient on I1_OccTenSq is insignificant in all wage regressions, see Table 2.

Table 10: Parameters Obtained Through Calibration

p_{1g}	0.3099	p_{1b}	0.2842
p_{2g}	0.4355	p_{2b}	0.2740
p_{3g}	0.5336	p_{3b}	0.2882
p_{4g}	0.4312	p_{4b}	0.3285
p_{5g}	0.4594	p_{5b}	0.2974
ϕ	4.92	ϕ'	2.34
σ	8.65	σ'	11.33
γ	0.7933		

NOTES: Occupations 1 to 5 correspond to Professional, Technical, Service, Craft, and Operators, respectively.

Table 11: Fraction of Occupational Mobility Distributions Accounted For: Experiment 1 (%)

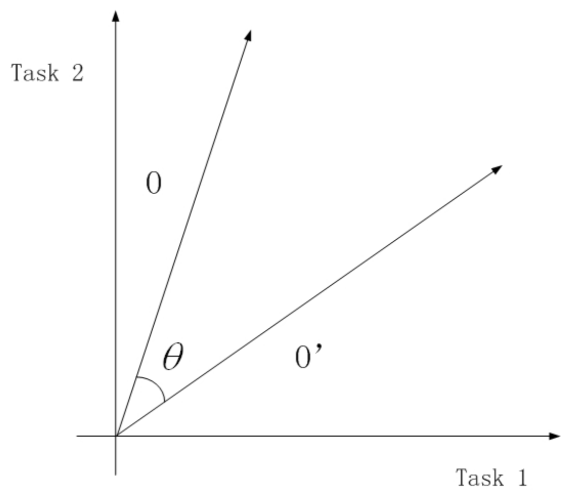
Model	Fraction
Benchmark	65.46
Without idiosyncratic shocks	10.91
Without aggregate shocks	65.45

Table 12: Fraction of Distributions Accounted For: Experiment 2 (%)

Model	Mobility	Duration
Benchmark	65.46	76.30
Without Mobility Costs	49.55	76.45
Without Search Frictions	65.16	0
TransferRates = 100%	60.91	76.68

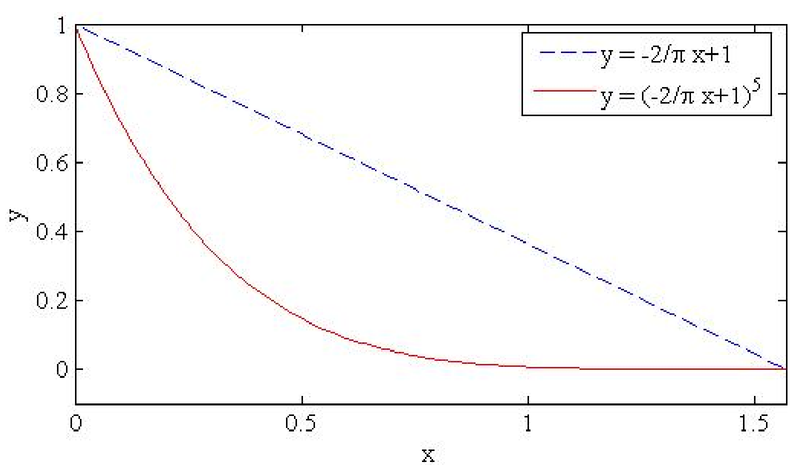
NOTES: Mobility and Duration refer to the occupational mobility distributions and transition duration distributions, respectively.

Figure 1: Distance Between Occupations: 2-Task Case



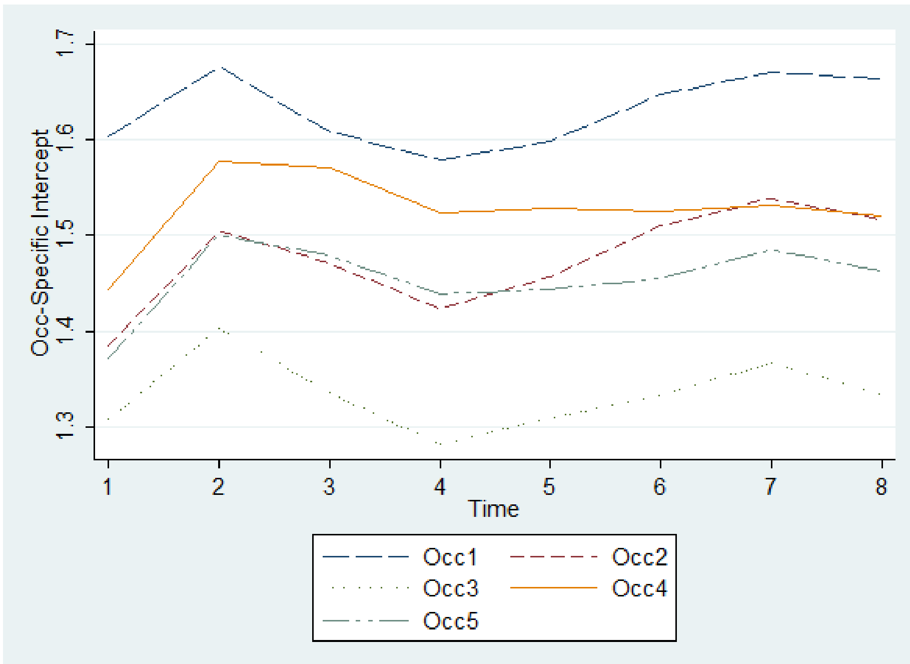
NOTES: The distance between source occupation O and target occupation O' is measured by θ, the angle formed by them. The bigger θ is, the farther the 2 occupations are from each other. $\theta \in [0, \pi/2]$.

Figure 2: Transfer Rate Function



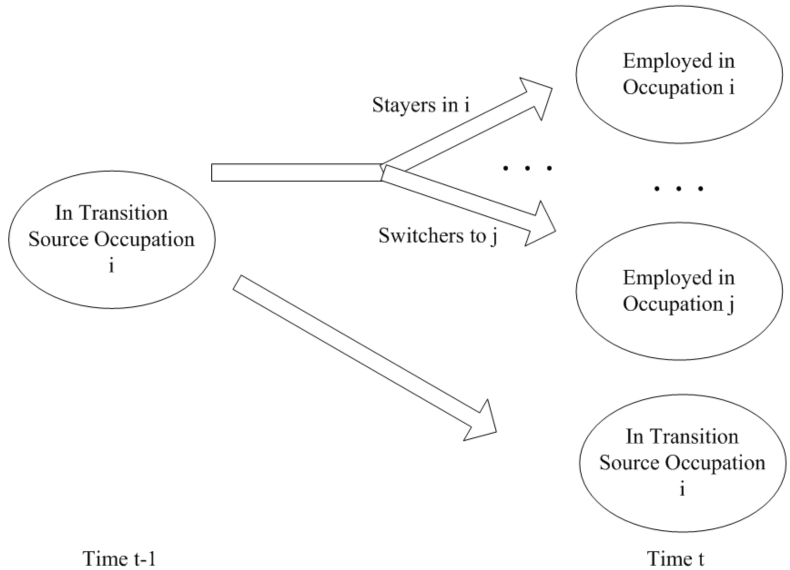
NOTES: The Transfer Rate function $y = (-\frac{2}{\pi}x + 1)^5$ is convexly decreasing. It is transformed from the linear function $y = -\frac{2}{\pi}x + 1$.

Figure 3: Occupation-Specific Intercepts



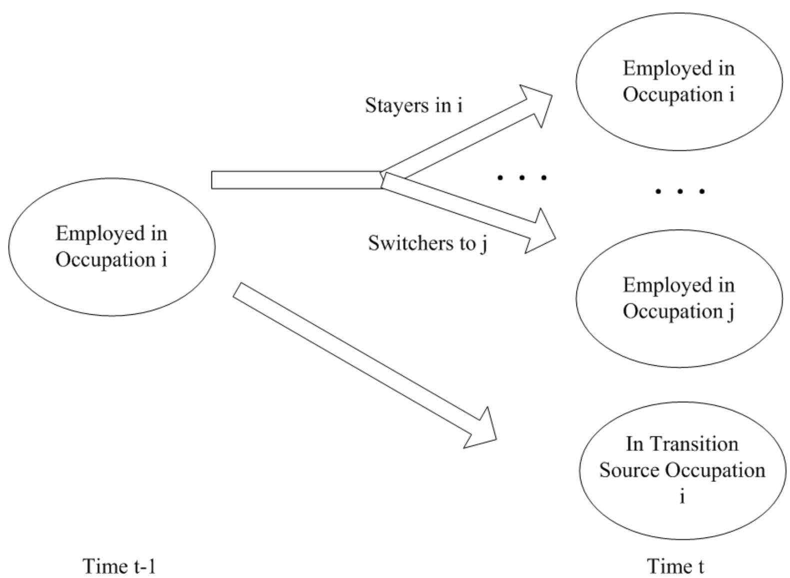
NOTES: The figure plots occupation-specific intercepts against time. The intercept returns of 5 occupations are positively correlated, moving in same directions at all times. Occupations 1 to 5 correspond to Professional, Technical, Service, Craft, and Operators, respectively.

Figure 4: Flow Chart for Off-Job Search Workers



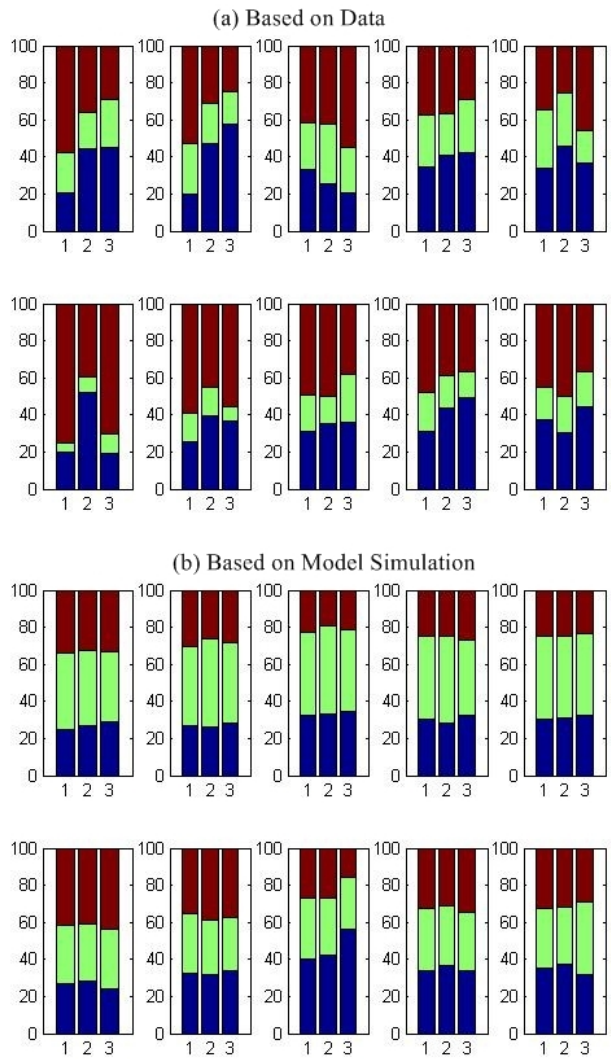
NOTES: Workers who are in transition at time $t-1$ with source occupation i may end up at time t being employed in their source occupation i, or being employed in a different occupation j, $j \neq i$, or continuing to stay in transition.

Figure 5: Flow Chart for On-the-Job Search Workers



NOTES: Workers who are employed at time $t-1$ with source occupation i may end up at time t being employed in their source occupation i, or being employed in a different occupation j, $j \neq i$, or flowing to transition.

Figure 6: Transition Time Distributions



NOTES: This figure demonstrates the transition time distributions across different subgroups and under different aggregate shocks. Part(a) is based on data and and Part(b) model simulation. Each part consists of 10 panels, with the top row depicts situations under good shocks and bottom row bad shocks. The 5 panels on each row, from left to right, correspond to Occupations 1 to 5: Professional, Technical, Service, Craft, and Operators, respectively. The 3 stacked bars in every panel represent 3 different skill levels from left to right: low, medium, and high. Each bar has 3 sections and they, from bottom to top, show the fractions of workers who experience short (4 months), medium (8 months or 1 year), and long (more than 1 year) transition periods, respectively.

Figure 7: Calibration Algorithm

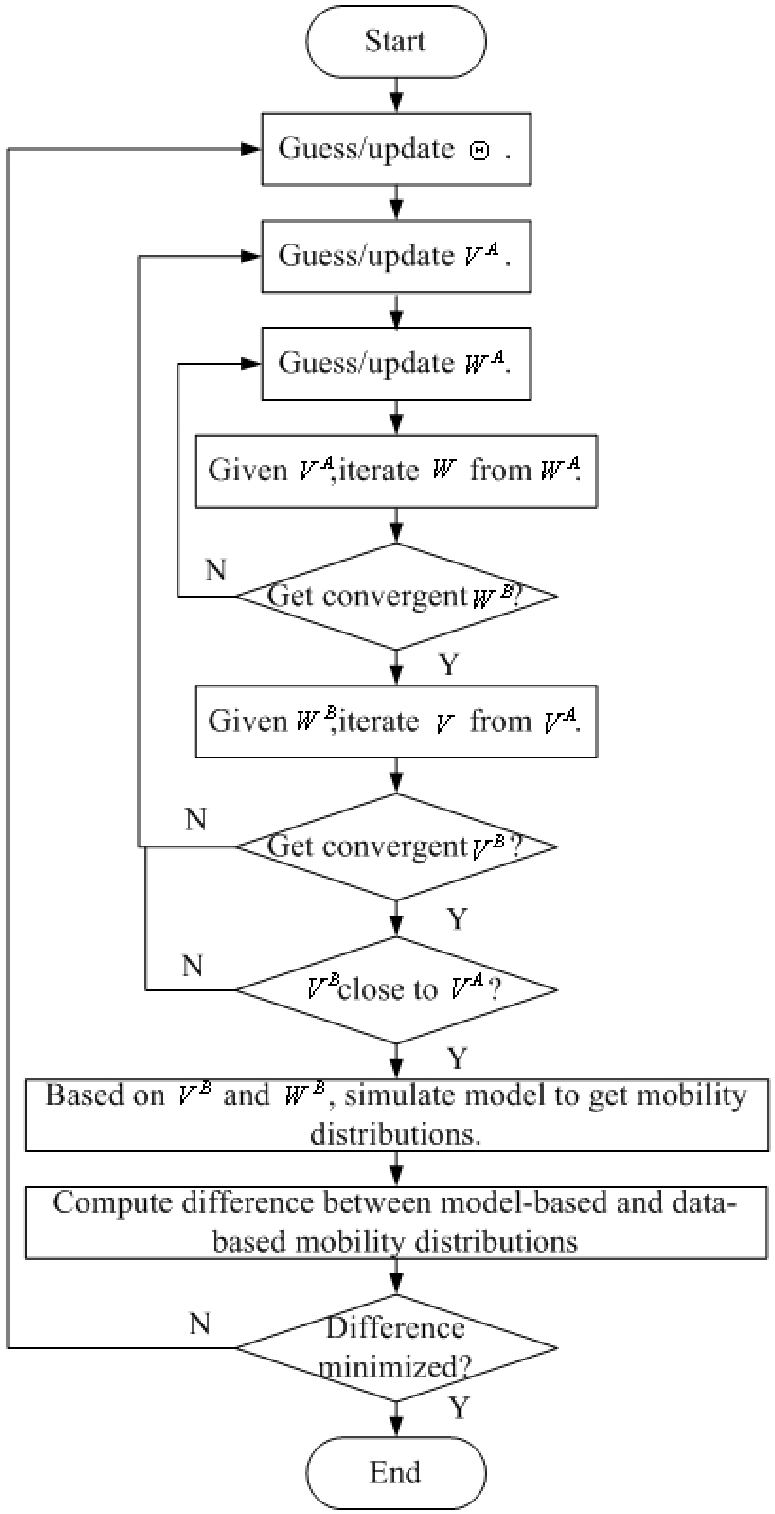
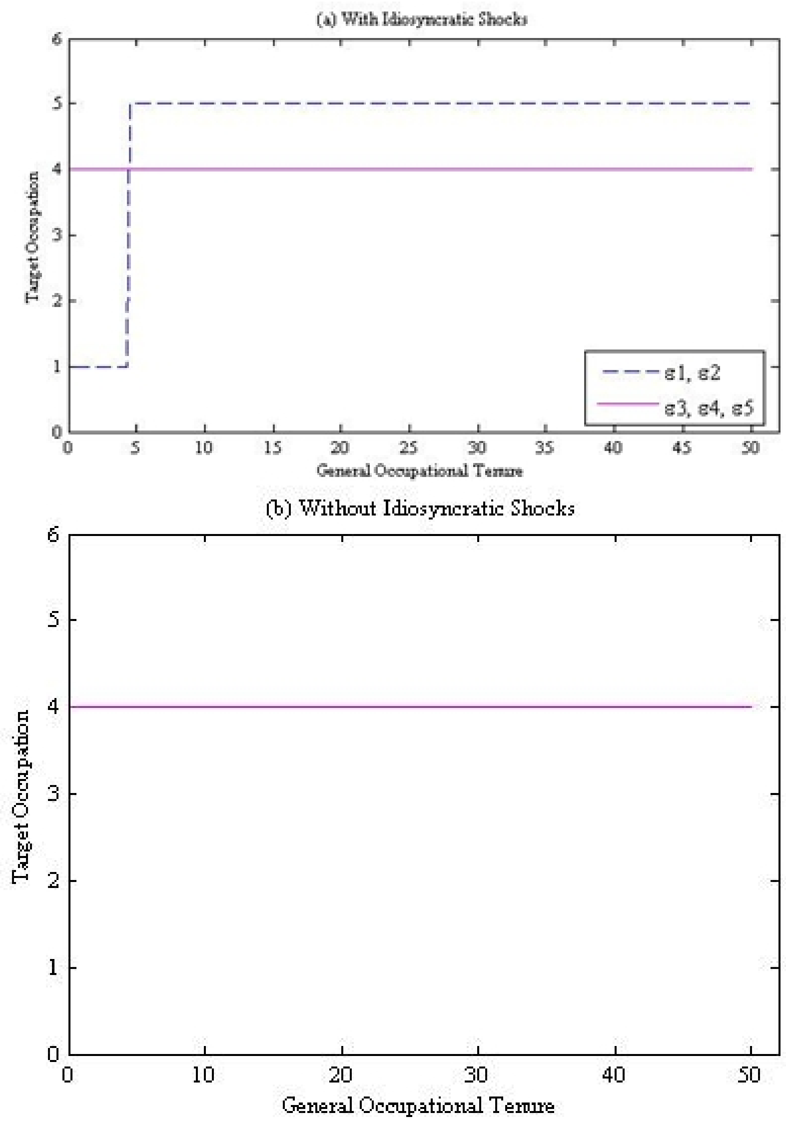
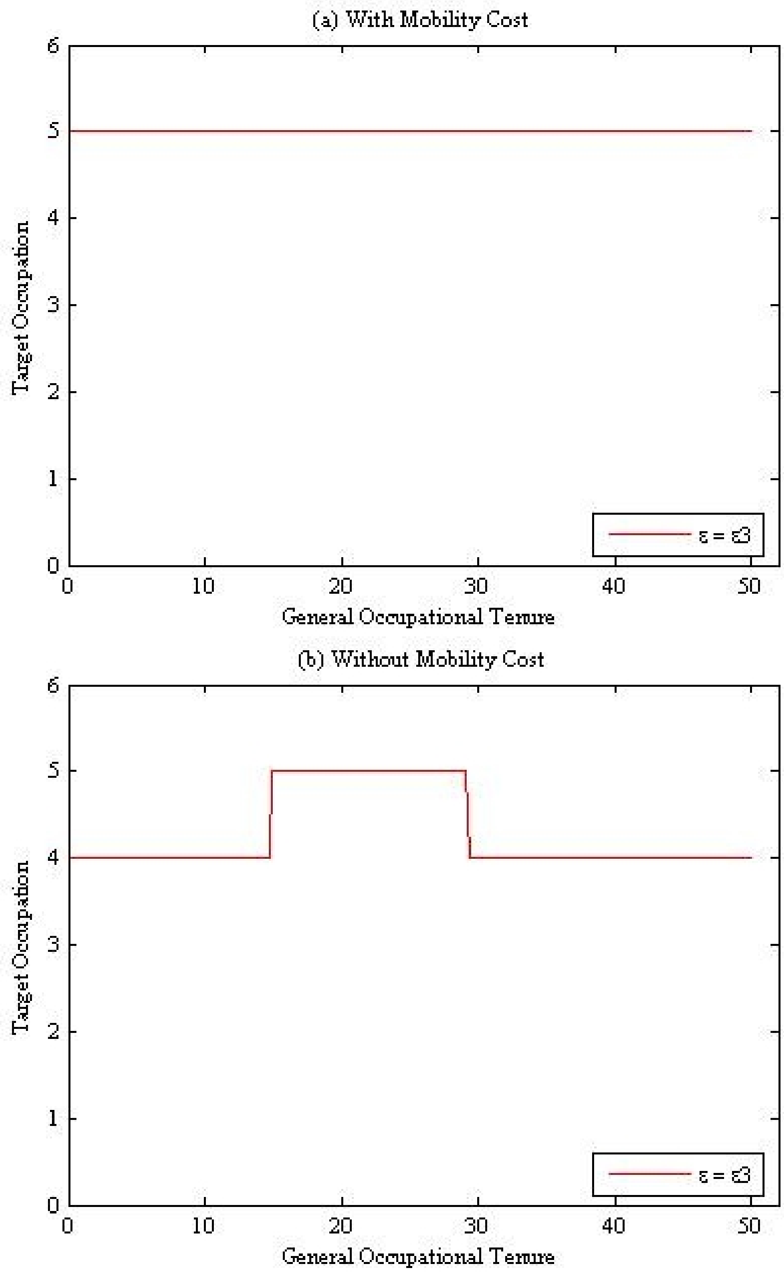


Figure 8: Policy Function: Off-Job Search Craft Workers in Bad Times



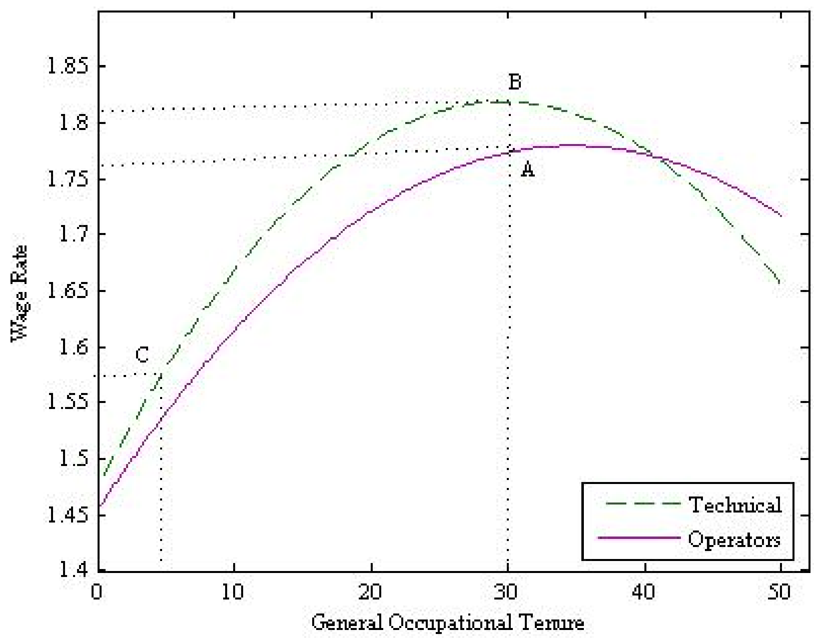
NOTES: ϵ's 1 to 5, from small to large, are 5 realizations of the idiosyncratic shock. Occupations 1 to 5 correspond to Professional, Technical, Service, Craft, and Operators, respectively.

Figure 9: Policy Function: On-The-Job Search Operators in Good Times



NOTES: The idiosyncratic shock ϵ takes on the value of $\epsilon 3$, or zero. Occupations 1 to 5 correspond to Professional, Technical, Service, Craft, and Operators, respectively.

Figure 10: Transfer Loss during an Occupational Switch



NOTES: The figure plots the log wage as a function of the General Occupational Tenure for 2 occupations, Technical and Operators. Consider an operator with 30 years of General Occupational Tenure. His current log wage is 1.77 at Point A. If he thinks of switching to Technical, without a transfer loss he will carry 100% or 30 years of General Occupational Tenure to the new occupation and receive a log wage of 1.82, which is represented by Point B. However, in case the transfer loss exists, he can transfer only 16% or 4.8 years of General Occupational Tenure to Technical, according to the Transfer Matrix, and thus earn a log wage of 1.58, indicated by Point C. Hence he will give up the idea of switching.