Moving for Better Skill Match *

Mariana Odio-Zuniga† C. Y. Kelvin Yuen‡

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Abstract

This paper studies the connection between multidimensional skill mismatch and labor mobility decisions, and the implications on the aggregate economy thereof. We show empirically that higher skill mismatch induces workers to move to a better matched job. Moreover, labor mobility helps reduce skill mismatch, especially for those previously with high skill mismatch. An equilibrium search model featuring skill mismatch and on the job search is developed. Quantitatively, we find that (i) skill mismatch has an important role to play in affecting the labor mobility decisions, as well as the aggregate economy, (ii) about two-thirds of the total skill mismatch can be accounted for by search frictions, which explain half of the occupational mobility and cost about 1% of the aggregate output and welfare, and (iii) aggregate productivity growth has positive impact on both the skill mismatch and occupational mobility.

JEL classification: E24, J24, J61, J62, J64

Keywords: multidimensional skill mismatch, occupational mobility, geographical mobility, job separation, search, matching

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†Department of Economics, Washington University in St. Louis, Campus Box 1208, One Brookings Drive, St. Louis, MO 63130. Email: m.odioz@wustl.edu.

‡Department of Economics, Washington University in St. Louis, Campus Box 1208, One Brookings Drive, St. Louis, MO 63130. Email: kelvinyuen@wustl.edu.

1 Introduction

The performance of the aggregate economy is inherently intertwined with that of the labor market. Labor market outcomes, in turn, are directly affected by the quality of firm-worker matches. When the worker's skill set and the skill requirement needed to properly execute a job do not perfectly align, skill mismatch exists in the match hurting the productivity of the worker. In this case, there is incentive for the worker to move to a better match which is welfare-improving and could have important aggregate consequences.

The view of workers self-selecting into jobs where they have comparative advantage in dates back to Roy (1951). The literature has evolved towards a notion of heterogeneous human capital instead of a general human capital concept, which has allowed the explanation of a variety of labor market outcomes that the traditional models could not (Sanders and Taber, 2012; Acemoglu and Autor, 2011). It has been well documented that the best possible match between workers and employees is always desired for both parts. Workers use job experience to determine both how they match with possible careers as well as how they match with specific firms. Therefore, they have an incentive to postpone search over firms until they are fairly confident that their career match is a good one (Neal, 1999).

More recently, considering workers' skills as multidimensional and how they align with respect to a job's skill requirements has been emphasized by many in the literature[1]. There are a few reasons why a multidimensional skill construct can be more appropriate to explain labor mobility. First, jobs differ in their requirements of particular skills which is at odds with the notion of a one-in-all skill. Hence, by allowing workers to have bundles of different skills used in varying proportions according to their job, one can justify the occupational choice decisions according to their relative intensity of skills. Second, by using an overall measure of skills, unobserved heterogeneity is overestimated and one would overlook the cost of surplus arising from skill mismatch when an under-qualified or over-qualified individual is hired (Lise and Postel-Vinay, 2020)[2]. Finally, a one-in-all skill measure for workers is only valid when there exists a sufficiently high correlation between all the skills that a worker might possess. The correlation between skills are, however, far from perfect, and hence it would be misleading to use a one-dimensional skill measure by ignoring the correlations between skills[3].

[1]See, e.g., Guvenen et al. (2020) and Lise and Postel-Vinay (2020), and the references therein.

[2]Lindenlaub and Postel-Vinay (2020*a*) show that a model where heterogeneity is measured as a one-dimensional object is misspecified and often yield misleading estimates of sorting and mismatch.

[3]We follow Guvenen et al. (2020) to define a worker's math, verbal, and social skills. In the NLSY79, social skill has a correlation coefficient of 0.34 and 0.36 with math and verbal skill, respectively.

While the negative effects of skill mismatch on the individual's outcomes, such as employment and wages, have been clearly established in the literature, it remains unexplored how skill mismatch affects the aggregate economy as a whole and how public policies mitigate the costs of skill mismatch to overcome these negative outcomes. A possible channel to analyze the impact of skill mismatch is through labor mobility. Intuitively, facing a large skill mismatch in the labor market, workers have the incentive to move to jobs better matched with their skill set. This affects both their labor mobility and job separation decisions as well as the firm entry decision, which would in turn have important general equilibrium consequences for the aggregate economy.

Figure 1a shows the increasing time trend of skill mismatch in the United States labor market. This trend is likely due to aggregate productivity growth as we controlled for the demographic variables. Second, at the aggregate level, a positive correlation between occupational mobility and skill mismatch is observed (see Figure 1b). To explain these aggregate relationships, a general equilibrium macroeconomic framework featuring multidimensional skill mismatch and labor mobility is needed. This paper attempts to fill this gap in the literature by analyzing and quantifying the relationship between skill mismatch and labor mobility decisions, as well as the aggregate implications thereof.

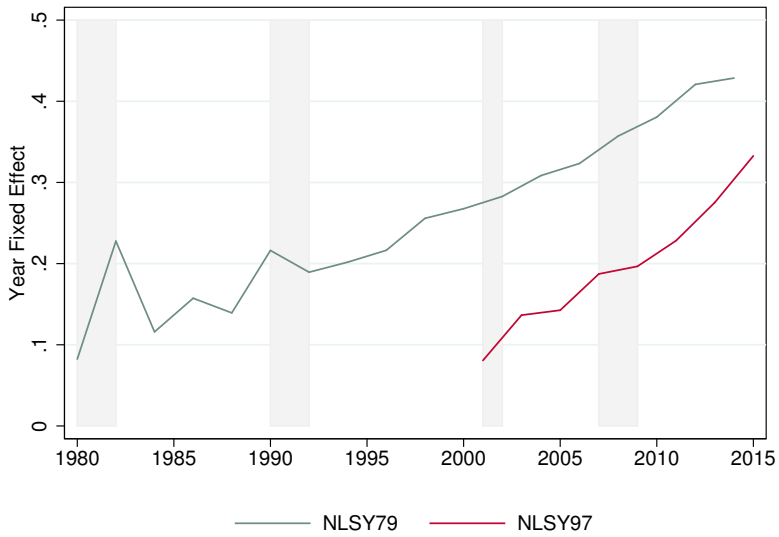
To this end, using data from the NLSY79 and NLSY97 jointly with the O*NET[4], we start by empirically studying the impact of skill mismatch on individual's decisions of migration, occupational choice and job separation. Through a regression analysis the empirical findings are as follows. First, higher skill mismatch has positive effects on occupational mobility, geographical mobility and job separation. Second, positive mismatch (over-qualification) presents a strong positive effect on mobility. However, the effects of negative mismatch (under-qualification) on occupational and geographical mobility are less clear, though it has a negative effect on job separations. Third, in general, mobility helps reduce skill mismatch, especially for those workers in the 90th percentile.

We develop a model to understand at the aggregate level, how does this connection relates to the aggregate performance of the economy, such as output and employment, and, in turn, the impact of aggregate productivity growth and public policies on the skill mismatch and labor mobility. Specifically, we construct an equilibrium search and matching model (Mortensen and Pissarides, 1994) featuring on the job search and multidimensional skills

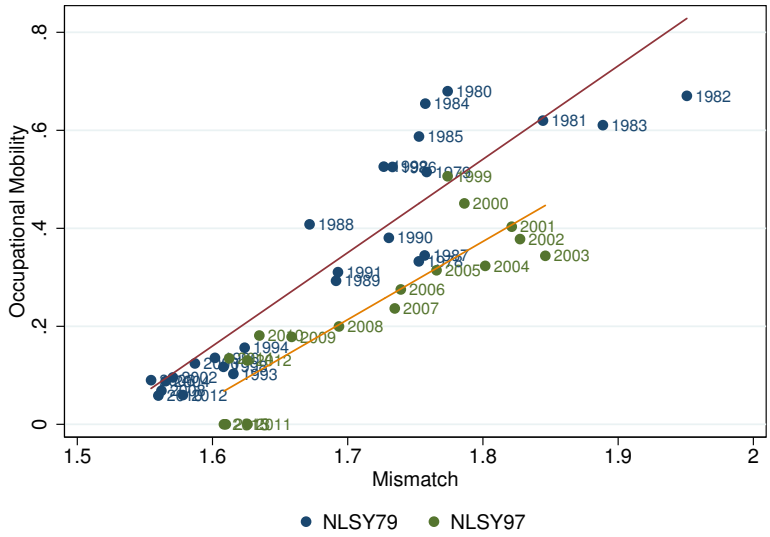
[4]We combine the skill and occupation information from the NLSY79/97 data, geographical information from the NLSY Geocode, and job requirements from the O*NET data to construct both skill mismatch and mobility measures. See Section 3 for detailed definitions.

Figure 1: **Occupational Mobility and Skill Mismatch by Year**

(a) Time Trend of Skill Mismatch



(b) Occupational Mobility and Skill Mismatch



Notes: See Section 3.2 for the construction of the skill mismatch measure. Occupational mobility is defined as the change of occupation from one year to another accompanied by a job switch. *Figure (1a)*: Gray shaded area indicates periods of recession in the United States. The Y-axis values correspond to the coefficient of each year fixed effect of a regression of skill mismatch controlling for age, age-squared, gender, race, education and year fixed effects. *Figure (1b)*: Each dot corresponds to the relationship between overall mismatch and occupational mobility in each year by cohort. The straight lines in the figure corresponds to the fitted line for each cohort.

and job requirements to meaningfully discuss the role of skill mismatch and labor mobility in the aggregate labor market. In the model, workers differ by their skills, and jobs differ by their requirements which are not binding. This environment entails that there are two sources of skill mismatch. First, skill mismatch naturally arises due to search frictions since workers may not be able to find the best match job due to random matching. Second, at the aggregate level, the imperfect correlation between skills and the differential distributions among skills and job requirements make it impossible to have a perfect match for every worker in the economy. We show that if, other things equal, skill mismatch reduces total match surplus by lowering the joint product, then higher skill mismatch would imply higher occupational mobility. Intuitively, when an individual's skill mismatch measure is high, there is a higher chance that she is able to receive a job offer with a higher match surplus. As a result, she is more likely to move to a job with a better skill match.

The model is calibrated to the United States labor market to study the quantitative effect of skill mismatch and labor mobility on the aggregate economy. The main findings from our quantitatively analysis are as follows. First, one standard deviation increase in the skill mismatch is associated with 0.7% increase in the monthly occupational mobility rate. The possibility of occupational mobility has a large quantitative impact on the aggregate skill mismatch and unemployment rate. When occupational mobility is not allowed, the average skill mismatch would increase by about 10%, while the unemployment rate would be about one percentage point lower. Also, income inequality would increase by more than 1% for the employed workers. Moreover, we find that the multidimensionality of skills hinders the improvement of skill mismatch by switching jobs. Hence, a one-dimensional model tends to overstate the effects of occupational mobility on skill match. Second, we find that search frictions account for about two third of the total skill mismatch. Also, skill mismatch due to search frictions contributes to almost half of the occupational mobility rate and costs about 1% of the aggregate output and welfare. Third, by introducing on-the-job learning, we show that human capital accumulation is important for both skill mismatch and occupational mobility. We find that average skill mismatch is decreasing in the rate of on-the-job learning, which promotes assortative matching between workers and jobs and disincentivizes occupational mobility. Quantitatively, a 1% rate of learning would cut the occupational mobility rate in half and translate to an 8% drop in average skill mismatch, as the workers become more sorted to their job.

We find that as the aggregate productivity increases, skill mismatch in the economy gets mildly more severe, while the occupational mobility rate becomes significantly higher. More-

over, as the total match surplus increases, firms have more incentives to create vacancies and enter the market which increases the job-finding rate. Since there are more jobs available in the economy, it is more likely that an employed worker would be able to find a better-matched occupation in the market. Thus, the occupational mobility rate becomes larger, and the unemployment rate becomes lower, while total output increases. We find that a 20% growth in aggregate productivity would lead to a 2% increase in the average skill mismatch.

Finally, we evaluate the impact of an increase in unemployment benefits on the economy. We find that as the unemployment benefits increase by 10%, the aggregate mismatch rises by 5% and the occupational mobility rate decreases from 0.9% to 0.76%. Intuitively, when the unemployment benefit is higher, the outside option of the workers become more valuable. As a result, fewer matches carry a positive surplus and so there are fewer jobs available to search. Therefore, the probability of meeting with a job with a positive surplus decline, leading to a lower occupational mobility rate. This leads to a large increase in the unemployment rate as well as an 8% drop in total output.

The remainder of the paper proceeds as follows. Section 2 discusses the related literature and the contributions of this paper. Section 3 presents the construction of the multidimensional skill mismatch measure and the empirical findings. Section 4 builds the equilibrium model of skill mismatch and labor mobility while Section 5 shows the calibration of the model and quantitative analysis of the impact of skill mismatch and mobility on the aggregate economy. Section 6 concludes.

2 Related Literature

This paper relates to two branches of the skill mismatch literature. First, skill mismatch can be measured by comparing the education level of the workers and education requirement of the jobs. This has been used, for example, to study the risky investment of choosing to go to college which explains why the enrollment and graduation rates were unresponsive to the rising college wage premium (Lee, Shin and Lee, 2015). Also, Shephard and Sidibe (2019) studies the effects policies designed to increase the supply of education on the mismatch between workers and firms. Second, as mentioned above, there is the skill mismatch arising from multidimensional skills and requirements. In particular, a set of papers has been written highlighting the effect of skill mismatch at the individual level such as entry wages,

employment decisions, wage growth, sorting and occupational choices[5]. For example, Guvenen et al. (2020) constructs a mismatch measure which emerges from a dynamic model of occupational choice with multidimensional skill accumulation and Bayesian learning about abilities. Workers enter the economy with imperfect information about their true abilities to acquire different types of skills and overtime learn which are their strengths and weaknesses. They subsequently choose an occupation taking this new information into account leading to lower mismatch over time (similar arguments are done by Kambourov and Manovskii, 2008, Kambourov and Manovskii, 2009*a*, Sanders, 2016, and Gervais et al., 2016). Using their structural model, they construct an empirical measure of skill mismatch using data from workers and occupations. We contribute to this second strand of the literature by developing a general equilibrium search and matching model discussing the role of skill mismatch and labor mobility in the aggregate economy.

We also contribute to the literature regarding job mobility, i.e. occupational mobility, geographical mobility and job separation. In the United States for the period span of 1968 to 1997, occupational mobility has increased (Kambourov, Manovskii and Plesca, 2018). However, this increasing rate has slowdown due to different factors such as the composition of the population, and distribution of wages (Moscarini and Thomsson, 2007 and Molloy, Smith and Wozniak, 2020)[6]. Also, switches can be costly. Lindenlaub and Postel-Vinay (2020*b*) argues that the worker-surplus drives workers' employment transitions through observable worker and job characteristics in the United States, which is necessary to understand the extend of mismatch and the corresponding welfare loss[7]. To the best of our knowledge, there exist just a few papers exploring the relationship between occupational mobility and the aggregate economy. For instance, Dvorkin and Monge-Naranjo (2019) show that task-biased technical improvements can explain occupational mobility in the United States as well as the increase in the capital share of income, labor market polarization, and earnings inequality. Meanwhile, Hsieh et al. (2019) show that in the United States between 20% and 40% of growth in aggregate market output per person can be explained by the improved allocation of talent. Finally, job separation is strongly related to mismatch among inexperienced workers rather than among experienced workers (Fredriksson, Hensvik and Skans, 2018).

[5]See, for example, Guvenen et al. (2020), Lise and Postel-Vinay (2020), Fredriksson, Hensvik and Skans (2018) for Sweden, Lindenlaub (2017), Yamaguchi (2012), Golan, James and Sanders (2019), and the references therein.

[6]Groes, Kircher and Manovskii (2015) show that in Denmark the low wage and the high wage workers within an occupation are more likely to leave that occupation; yet, they argue that these patterns translate to the US economy as well.

[7]For a further discussion regarding the cost of occupational mobility refer to Cortes and Gallipoli (2018).

Finally, in regards to geographical mobility, the inter-state and inter-county migration has decreased steadily since the eighties; which has been argued that workers find it less desirable to switch employers since the net benefits of relocating have decreased (Molloy, Smith and Wozniak, 2017). Even if the geographical change occurs, the improvement of the economic status of individuals by producing better job matches is very small (Rodgers and Rodgers, 2000; Kothari, Saporta-Eksten and Yu, 2013). We contribute to this strand of the literature by analyzing the role of mismatch on geographical mobility when an occupational switch occurs. We argue that people might relocate to find a better job match given that the distribution of jobs vary by geographic region expanding their horizons. However, in line with the literature, we find that moving to a different location has little effects on improving skill mismatch and on average individuals with higher skill mismatch (over-qualified) are more likely to relocate.

3 Empirical Analysis

In this section, we define and construct an empirical measure of multidimensional skill mismatch[8]. We then present the empirical framework to analyze the relationship between skill mismatch and labor mobility decisions. Analyzing what happens when skill mismatch changes allows us to see at the micro level the factors affecting the mobility decision of an average worker. The empirical relationship between skill mismatch and labor mobility motivates the theoretical model in Section 4, where we explore the economic mechanism behind the empirical findings.

3.1 Data

Workers' information is taken from the *National Longitudinal Survey of Youth 1979* (NLSY79) which is a nationally representative sample of individuals who were between 14 and 22 years old in 1979. To explore possible changes in behavioral patterns, we also use the *National Longitudinal Survey of Youth 1997* (NLSY97) which includes individuals who were between 12 and 16 years old at the end of 1996. The sample period spans from 1978 to 2014 for the NLSY79 sample and from 1997 to 2015 for the NLSY97 sample. The final sample has information regarding demographic characteristics of each individual and their labor force status

[8]Refer to Appendix A for a more detailed description of the data construction.

using their primary job information such as occupation, weekly and annual hours worked, wages[9], and job separation. Given that occupations are coded differently throughout the years, we transform all occupations using the Census 1990 Three-Digit Occupation Code.

The sample is restricted to individuals with age greater or equal to 16 years old who are not currently enrolled in any educational institution. Given these sample restrictions, we end up with 11,914 individuals with an average age of 37 years old (58 for the oldest) and 410,179 individual-year observations for the NLSY79 cohort; and 6,889 individuals with an average age of 25 (35 for the oldest) and 81,014 individual-year observations for the NLSY97 cohort. Table A.2 in the Appendix shows the demographic composition of our sample for both cohorts in the first and sixth column, respectively. Besides presenting summary statistics for different gender, race and marital status, we consider four age groups (less than 25, 25-34, 35-44 and greater or equal than 45 years old) and five educational levels (high school dropout, completed high school, some college, completed 4-year college, greater than 4-year college).

On the workers side, following Guvenen et al. (2020) and Lise and Postel-Vinay (2020), we use the *Armed Services Vocational Aptitude Battery (ASVAB)*[10], the Rotter Locus of Control Scale and Rosenberg Self-Esteem Scale (for NLSY79) and several personality scales (for NLSY97) to construct skill measures. On the firm side, we use the O*NET data regarding scores on skills, abilities and knowledge for each occupation[11]. The combination of these two data sources, NLSY and O*NET, has been a common denominator in the literature and allows for the construction of the empirical skill mismatch measure for each worker-occupation pair.

3.2 Mobility and Multidimensional Skill Mismatch Measures

Labor Mobility We define three mobility indicators: occupational mobility, geographical mobility and job separation. It is well-known that the US data has plenty of measurement error due to occupations and/or jobs being miscoded from one interview year to another (Kambourov and Manovskii (2009*b*)). Taking this issue into consideration, we follow Kambourov, Manovskii and Plesca (2018) and Moscarini and Thomsson (2007), where only "genuine"

[9]All wages are deflated to 2000 price level using the US Consumer Price Index.

[10]The ASVAB is a multi-aptitude test for occupational placement. The same 4 components as in Guvenen et al. (2020) to create the verbal and math ability measure are used: Word Knowledge, Paragraph Comprehension, Arithmetic Reasoning and Mathematics Knowledge.

[11]We use the same 26 descriptors for the math and verbal component and 6 descriptors for the social component, as in Table A.1 in Guvenen et al. (2020).

occupational switches are considered; this is, *occupational mobility* occurs when a change of occupation from one year to another is accompanied by a job switch as well[12]. For the case of geographical switches we use the *NLSY Geocode Data* restricted data set where for each individual's county of residence we identify a commuting zone using the 2000 commuting zone clustering from the U.S. Department of Agriculture. *Geographical mobility* occurs when an individual moves from their current residence commuting zone to a different commuting zone and such switch is accompanied by changes in occupation and job as well[13]. Finally, *job separation* is defined as the transition from being employed to non-employed from one interview year to another (refer to Table A.2 to see the summary statistics for these mobility rates).

Skill Mismatch The skill mismatch measure of this paper closely follows the procedure introduced by Guvenen et al. (2020). Worker's abilities and requirements are aggregated into three skill components: Verbal, Math and Social, using the abilities and requirements information in NLSY79(97) and the O*NET[14]. Hence, *skill mismatch* occurs when the worker's abilities does not perfectly align with the skill requirements of a job. If a particular ability component of a worker is above the corresponding occupation requirement, we say that the individual is over-qualified and possesses *positive mismatch* in that skill component. Vice versa, if the individual is under-qualified, then there is *negative mismatch*.

For the empirical measure of the skill mismatch, let i be an index for individual and j an index for each skill dimension (verbal, math, social). Denote $c(i)$ as the occupation of the individual i, $A_{i,j}$ as the measured ability of individual i in skill j and $r_{c(i),j}$ the measured skill requirement of occupation $c(i)$ at skill j. Then, the j component mismatch of the worker i is define as

$$m_i^j = \left| q(A_{i,j}) - q(r_{c(i),j}) \right| \tag{1}$$

where $q(\cdot)$ corresponds to the percentile ranks of abilities or requirements. Therefore, the mismatch of each skill component is defined as the absolute distance of the worker's ability and the job requirement of her occupation. The overall *skill mismatch* is then the weighted

[12]Moscarini and Thomsson (2007) refer to this concept as job mobility and identify occupational mobility when a switch in occupation occurs but is not necessarily accompanied with a job switch.

[13]Since we are interested in job mobility, we control geographical mobility with an occupational switch. However, we also conducted the whole analysis with unconditional location switches and our findings are robust to such change.

[14]The NLSY97 does not have information regarding the Rotter Locus of Control Scale and Rosenberg Self-Esteem Scale. Instead, we use proxies from selected personality scales in the survey to construct the social component.

average of mismatch of each component:

$$m_i = \sum_{j=1}^{n} \left\{ \omega_j \times m_i^j \right\} \tag{2}$$

where ω_j are the weights over skill j. As in Guvenen et al. (2020) we use the factor loadings from the first principal component as weights.

To measure over- and under-qualification, overall skill mismatch is decomposed into *positive mismatch* and *negative mismatch*, respectively, as follows,

$$m_i^+ = \sum_{j=1}^{n} \left\{ \omega_j \times \max[m_i^j, 0] \right\} \tag{3}$$

$$m_i^- = -\sum_{j=1}^{n} \left\{ \omega_j \times \min[m_i^j, 0] \right\} \tag{4}$$

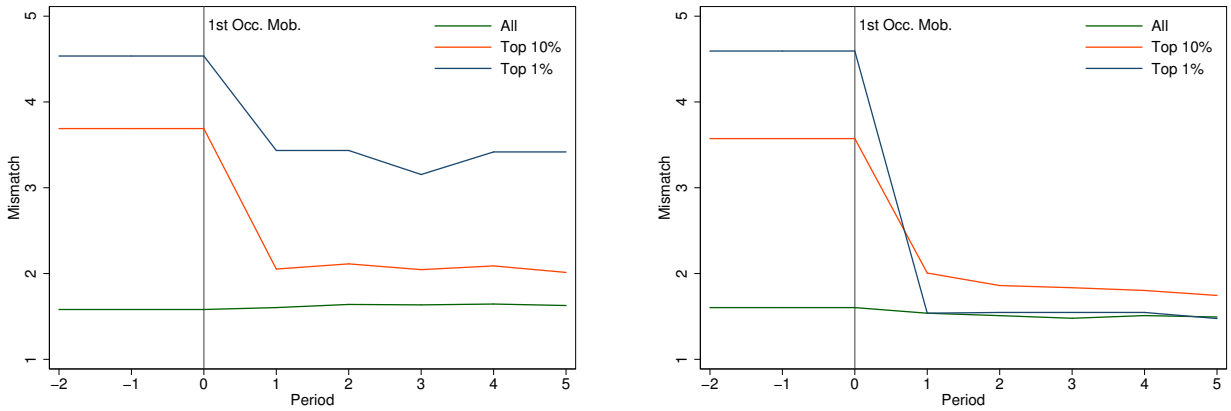
Finally, the distribution of skill mismatch by cohort is shown in Figure A.1 and the average of skill mismatch by demographic groups in Table A.2.

As an example, take an individual who is employed as a cashier with skill measures for math, verbal and social abilities, respectively: $0.1077, 0.2269$, and 0.2743. From the O*NET the skill measures requirements to be a cashier are, in the same order: $0.4944, 0.1635$, and 0.3882. Hence, overall skill mismatch under (2) equals 1.2836. Farther away from zero corresponds to bigger the misalignment between the set of skills of the worker and job requirements. We also see that this individual is over-qualified in the verbal component and under-qualified in the math and social components.

In Appendix D, we construct two alternative measures of mismatch using information from the wages of the workers. Specifically, we measure mismatch by the difference between the worker's wage and the ideal wage implied by a perfect match. Another mismatch measure would be the difference between the worker's and the job's fixed effects in the wage function. We find that the empirical measure proposed by Guvenen et al. (2020) and used in this paper has the most predictive value in our empirical analysis and provides results that are in line with the economic intuition regarding the relationship between skill mismatch and labor mobility (see below).

Figure 2: **Skill Mismatch Before and After Mobility**

(a) NLSY79 (b) NLSY97



Notes: See Section 3.2 for the construction of the skill mismatch measure. Occupational mobility is defined as the change of occupation from one year to another accompanied by a job switch. The event of interest at period 0 corresponds to the first occupational switch for the individuals in the sample. Figure (2a) and (2b) only takes into consideration individuals who are present in the sample with at least 8 consecutive years (2 periods prior to their first occupational switch and 5 periods afterwards) and whose mismatch measure is available for those years. For these individuals, the mismatch measure is only considered for every period prior to a second switch happening to be able to isolate the effect of only the first switch. The sub-samples "Top 10%" and "Top 1%" are composed by those individuals in the highest 10% and 1%, respectively, of the mismatch distribution at period -2.

3.3 Effects of Skill Mismatch on Labor Mobility

Due to search frictions, individuals may not be able to find the best matched job when they first enter the labor market. However, by switching occupations they will be able to find a better match, thereby reducing skill mismatch over time. Figure 2 shows for each cohort their mismatch level throughout 7 years. The x-axis shows the timeline relative to the " event" of interest (first occupational switch in the sample) occurring at time 0. We show the mismatch levels by initial mismatch percentiles. Upon the first occupational switch taking place we observe a significant drop in skill mismatch for those individuals in the top 10% and top 1% of the initial mismatch distribution. Hence, the worker-job's skill mismatch is in general improving via occupational mobility.[15].

We now proceed with the formal regression analysis. In doing so, we present a logit regression model where our outcome of interest is the probability of switching at period $t+1$ given an

[15]Guvenen et al. (2020) also argues that mismatched workers switch to improve their match quality; in particular, those who are overqualified tend to switch to occupations with higher requirements and vice versa for underqualified workers. They discuss that workers switches jobs to reduce skill mismatch and as they learn, their beliefs tend towards their true ability. Our evidence is consistent with such an argument, where individuals in both cohorts are switching to search for the "best" possible match given their set of abilities.

individual's characteristics and skill mismatch measure at time t. The logistic specification for mobility (occupational, geographical, job separation) is as follows

$$Mobility_{it+1} = \beta_0 + \beta_1 MM_{it} + \boldsymbol{\alpha X}_{it} + \theta_i + \epsilon_{it} \tag{5}$$

where for individual i in period t (yearly), $Mobility_{it+1}$ is a mobility dummy which equals 1 when the individual moves to a different occupation, geographic area, or transitions into non-employment at $t+1$. MM_{it} is the skill mismatch measure which includes the overall mismatch, positive and negative mismatch, and component-wise mismatch. $\boldsymbol{X}$ is a vector of controls that includes age, age squared, race, gender, marital status, educational group, and aggregate unemployment rate. Finally, θ_i corresponds to individual fixed effects.

Tables 1, 2 and 3 show the regression results for occupational mobility, geographical mobility and job separation, respectively [16]. In each table, columns (1) and (2) show the effect of overall mismatch, whereas (3) and (4) show the impact of positive and negative mismatch, and (5) and (6) show the effects of mismatch along each skill dimension.

On average we find that individuals with higher skill mismatch are more likely to switch occupations which is statistically significant after controlling for individual fixed effects. Table 1 also shows that when the mismatch empirical measure is decomposed into positive and negative mismatch, there is a positive effect on occupational mobility when individuals are overqualified. This means that workers continue searching for occupations to find a better-quality match given their abilities. This consistent with Fredriksson, Hensvik and Skans (2018), who argue that experienced workers suffer a wage penalty due to mismatch. Contrary to Guvenen et al. (2020) and Groes, Kircher and Manovskii (2015) where both overqualified and underqualified are more likely to switch, we have that the effect of negative mismatch is unclear, especially for the cohort of NLSY79, where the direction reverses after controlling for individual fixed effects.

To understand this, note that two effects are taking place and the sign of the coefficient will depend on which effect dominates. On the one hand, underqualified workers are experiencing a wage premium at their current match and thus do not have the incentive to switch the occupation; hence, a negative sign of the coefficient is expected. On the other hand, the shortfall of ability implies they are more likely to be laid off, motivating the workers to search for a job with a better match to their abilities. In this case, a positive sign of the

[16] See Appendix B, Tables B.1 and B.2 for the regression results of monthly occupational mobility and job separation.

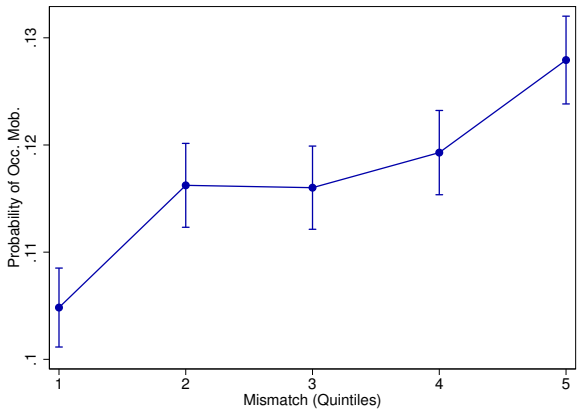
Table 1: **Regression Results: Occupational Mobility**

VARIABLES	(1) Logit	(2) Logit	(3) Logit	(4) Logit	(5) Logit	(6) Logit
			NLSY79			
Mismatch	0.0679***	0.0452***				
	(0.00821)	(0.0115)				
Positive Mismatch			0.104***	0.113***		
			(0.00955)	(0.0145)		
Negative Mismatch			0.0242**	-0.0220		
			(0.00985)	(0.0138)		
Verbal Mismatch					0.0485***	0.0275*
					(0.0110)	(0.0157)
Math Mismatch					0.0222**	0.0186
					(0.0110)	(0.0154)
Social Mismatch					0.0172**	0.0171
					(0.00840)	(0.0127)
Constant	2.806***		2.779***		2.798***	
	(0.171)		(0.171)		(0.171)	
Observations	131,130	98,613	131,130	98,613	131,130	98,613
Number of pid		6,257		6,257		6,257
			NLSY97			
Mismatch	0.0916***	0.0916***				
	(0.0109)	(0.0165)				
Positive Mismatch			0.120***	0.146***		
			(0.0125)	(0.0203)		
Negative Mismatch			0.0110	0.00128		
			(0.0135)	(0.0192)		
Verbal Mismatch					0.0658***	0.0826***
					(0.0142)	(0.0220)
Math Mismatch					0.0308**	0.0168
					(0.0142)	(0.0211)
Social Mismatch					0.0408***	0.0356**
					(0.0112)	(0.0173)
Constant	-6.218***		-6.302***		-6.264***	
	(0.442)		(0.442)		(0.443)	
Observations	53,089	44,061	53,089	44,061	53,089	44,061
Number of pid		4,525		4,525		4,525
Controls	YES	YES	YES	YES	YES	YES
Individual FE	NO	YES	NO	YES	NO	YES

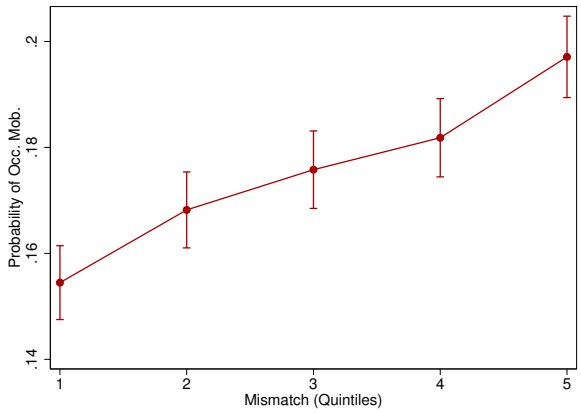
Note: Controls include age, age-squared, gender, race, completed education level, marital status, and unemployment rate at the national level. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Figure 3: **Predicted Mobility Rates**

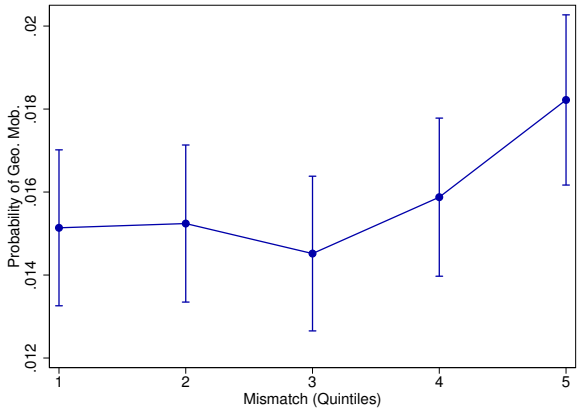
(a) Occupational Mobility: NLSY79



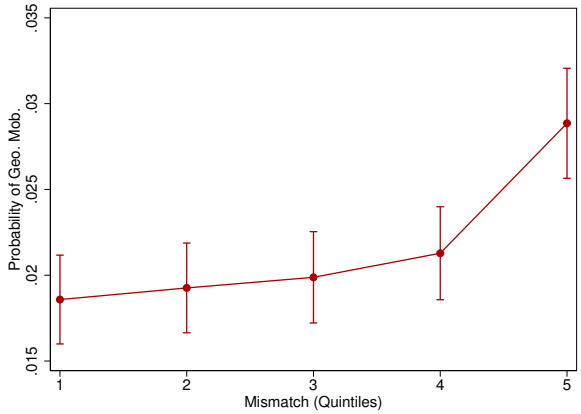
(b) Occupational Mobility: NLSY97



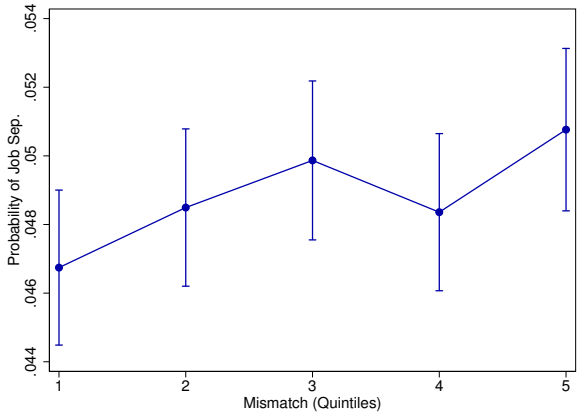
(c) Geographical Mobility: NLSY79



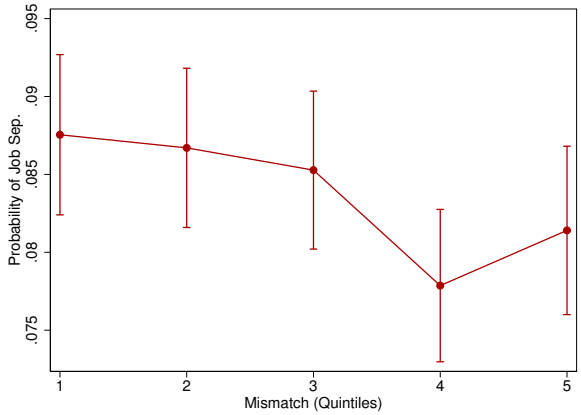
(d) Geographical Mobility: NLSY97



(e) Job Separation: NLSY79



(f) Job Separation: NLSY97



Notes: Geographical Mobility is conditional on an occupational switch occurring. The predicted probability is based on a Logit model with all controls. The vertical lines represent the confidence interval of the estimators at the 95% for each Mismatch Quintile.

coefficient is expected. Finally, when we consider mismatch for each dimension of skill, only verbal has a positive effect on occupational mobility for the NLSY79 cohort and is only significant at 10% level. For the cohort of NLSY97, the verbal and social mismatch components have a positive and significant effect on switching[17]. Figure 3a and 3b show the predicted probability of switching occupations for each skill mismatch quintile. The probability increases monotonically for each quintile and cohort. Noteworthy is that the younger cohort always has a higher probability of switching.

Table 2 shows the regression results of switching commuting zones and occupation. On average individuals with higher skill mismatch or those who are overqualified are more likely to relocate. However, this result is not robust to adding fixed effects for the cohort of NLSY79. Agents encounter a different distribution of jobs and skill requirements in different locations which opens the spectrum of possibilities for those individuals who are looking for a better match. The effect of each mismatch component on the probability of moving to a different commuting zone is unclear for the NLSY79 cohort; however, the math and social component are positive and statistically significant at 5% for the NLSY97 cohort. Figure 3c and 3d show the predicted probability of geographically re-locating for each skill mismatch quintile. The probability increases monotonically for each quintile. As previously noted, NLSY97 individuals tend to have higher probabilities of moving. Overall, we see that the mismatch effect tends to be stronger for occupational mobility than for geographical mobility.

Table 3 shows the regression results of the transition to non-employed. For the cohort of NLSY79, we have that the skill mismatch has a positive effect on the probability of separation of a worker from her primary job (see Figure 3e).

Also, on average, overqualified workers are more likely to separate from their jobs. This positive effect aligns with the fact that these workers search for a better match due to the wage penalty they experience [18]. Fredriksson, Hensvik and Skans (2018) also investigates the effect of mismatch on job separation for the population in Sweden and find that job separation has a higher response from mismatch for the inexperience workers, whereas the impact on experienced workers is small. These results do not seem to translate to the US economy,

[17]For full-time workers (i.e. worked at least 35 hours per week - before and after the switch) the results are shown in Table B.3. The effects of overall and positive mismatch hold and for negative mismatch continue to be unclear. After controlling for individual fixed effects, the individual components lose their significance for the cohort of NLSY79, yet for the cohort of NLSY97 the verbal component continues to have a positive and significant effect at 10%.

[18]When asked over-qualified individuals the reason behind their job separation, 55% answered "quitting", in contrast to 29% who got layoff by their employer.

Table 2: **Regression Results: Geographical Mobility**

VARIABLES	(1) Logit	(2) Logit-FE	(3) Logit	(4) Logit-FE	(5) Logit	(6) Logit-FE
			NLSY79			
Mismatch	0.0743***	0.0115				
	(0.0248)	(0.0349)				
Positive Mismatch			0.0891***	0.0146		
			(0.0274)	(0.0417)		
Negative Mismatch			0.0473	0.00736		
			(0.0325)	(0.0454)		
Verbal Mismatch					0.0507	0.0473
					(0.0327)	(0.0479)
Math Mismatch					0.0318	-0.0287
					(0.0337)	(0.0471)
Social Mismatch					0.000832	-0.0246
					(0.0256)	(0.0398)
Constant	-0.0844		-0.0923		-0.0740	
	(0.457)		(0.457)		(0.457)	
Observations	66,794	11,064	66,794	11,064	66,794	11,064
Number of pid		1,194		1,194		1,194
			NLSY97			
Mismatch	0.162***	0.158***				
	(0.0255)	(0.0377)				
Positive Mismatch			0.200***	0.190***		
			(0.0287)	(0.0442)		
Negative Mismatch			-0.00137	0.0839		
			(0.0367)	(0.0521)		
Verbal Mismatch					0.104***	0.0613
					(0.0350)	(0.0534)
Math Mismatch					0.0740**	0.103**
					(0.0353)	(0.0516)
Social Mismatch					0.0223	0.101**
					(0.0283)	(0.0425)
Constant	-12.86***		-12.99***		-12.87***	
	(1.298)		(1.297)		(1.298)	
Observations	47,749	9,274	47,749	9,274	47,749	9,274
Number of pid		1,049		1,049		1,049
Controls	YES	YES	YES	YES	YES	YES
Individual FE	NO	YES	NO	YES	NO	YES

Note: 1. Geographical mobility is conditional on an occupational switch occurring. Controls include age, age-squared, gender, race, completed education level, marital status, and unemployment rate at the national level. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table 3: **Regression Results: Job Separation**

VARIABLES	(1) Logit	(2) Logit-FE	(3) Logit	(4) Logit-FE	(5) Logit	(6) Logit-FE
			NLSY79			
Mismatch	0.0237**	0.0287*				
	(0.0110)	(0.0154)				
Positive Mismatch			0.0550***	0.0938***		
			(0.0129)	(0.0199)		
Negative Mismatch			-0.0159	-0.0293		
			(0.0132)	(0.0183)		
Verbal Mismatch					0.0128	0.00998
					(0.0143)	(0.0206)
Math Mismatch					0.0108	0.0247
					(0.0144)	(0.0202)
Social Mismatch					0.00996	-0.0121
					(0.0111)	(0.0166)
Constant	0.494***		0.466***		0.488***	
	(0.161)		(0.161)		(0.162)	
Observations	156,362	86,273	156,362	86,273	156,362	86,273
Number of pid		5,269		5,269		5,269
			NLSY97			
Mismatch	-0.0379**	0.00280				
	(0.0160)	(0.0288)				
Positive Mismatch			-0.0206	0.0842**		
			(0.0192)	(0.0384)		
Negative Mismatch			-0.0687***	-0.0656**		
			(0.0167)	(0.0291)		
Verbal Mismatch					0.00132	0.0381
					(0.0198)	(0.0368)
Math Mismatch					-0.0451**	-0.0332
					(0.0193)	(0.0346)
Social Mismatch					0.00681	0.00508
					(0.0149)	(0.0270)
Constant	-2.127***		-2.195***		-2.157***	
	(0.516)		(0.518)		(0.517)	
Observations	53,132	19,488	53,132	19,488	53,132	19,488
Number of pid		1,891		1,891		1,891
Controls	YES	YES	YES	YES	YES	YES
Individual FE	NO	YES	NO	YES	NO	YES

Note: Controls include age, age-squared, gender, race, completed education level, marital status, and unemployment rate at the national level. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

where for underqualified workers we do not find a robust effect of mismatch. Figure 3f does not show a clear and significant pattern for the predicted probability of job separation.

How do mismatch, wages, and weekly hours change after labor mobility? Figure 4 shows the change of labor market outcomes after mobility of these variables. First, when an occupational switch occurs, the deviation between abilities and requirements decreases for those who are at the top 10% of the mismatch distribution. Therefore, their skill mismatch level decreases[19]. We see the same pattern for those who are overqualified or underqualified and are in the corresponding top 10%. Hence, a switch in occupation benefits the most those at the right tail of the distribution; i.e. those who currently have jobs far from their true abilities and who by switching find a better match (see Figure 4a). Second, there is an increase in real wages after the switch, especially for those in the youngest cohort. The pattern is homogeneous independently from the mismatch percentile the worker is at (see Figure 4c)[20]. Finally, those in the top 10% of the distribution tend to work longer weekly hours after the switch which is especially true for the overqualified workers (see Figure 4e). This goes in line with Guvenen et al. (2020) who argue that occupational switches tend to be in the direction of reducing existing mismatch.

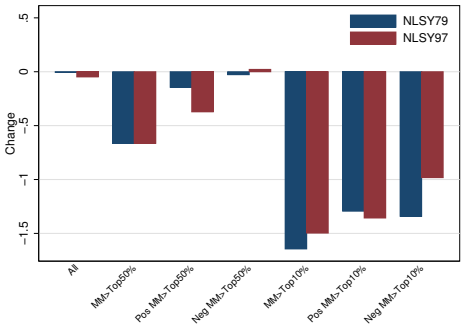
Now, besides having an occupational switch we consider geographical mobility as well. For both cohorts, individuals whose positive and negative mismatch scores are in the top 10% of the distribution still benefit the most in terms of finding an occupation that suits better their abilities. The change in wages continues to be homogeneous and those who relocate spend more weekly hours working. For those in the 50th percentile from the NLSY97, after they move to a different commuting zone, on average, they tend to work approximately 3.5 additional weekly hours. Yet, for those in the 90th percentile, we have opposite behaviors for different cohorts, i.e. those in the oldest cohort are working less than before but those in the youngest cohort are working more. Finally, for both cohorts, overqualified and underqualified workers are also working more after the switch.

[19] A negative change in mismatch means that there is a better match after the switch.

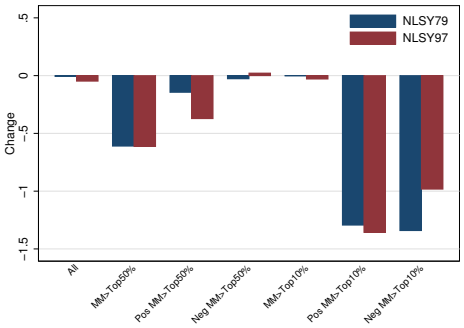
[20] The cases where negative/positive mismatch is greater than the top 10% are statistically different relative to the other cases, for both, the NLSY79 and NLSY97 cohort.

Figure 4: **Labor Market Outcomes After Mobility**

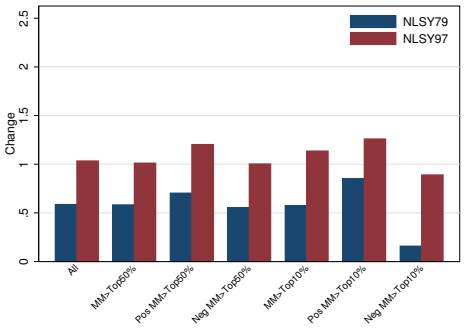
(a) Occupational Mobility: Change in Mismatch



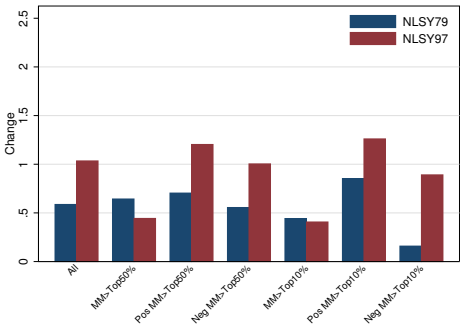
(b) Geographical Mobility: Change in Mismatch



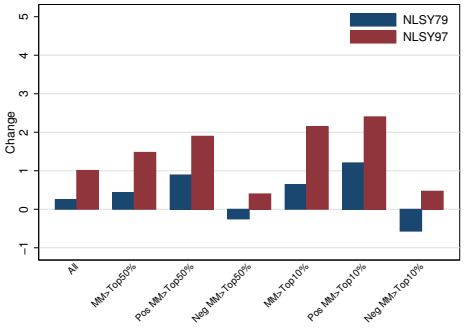
(c) Occupational Mobility: Change in Wages



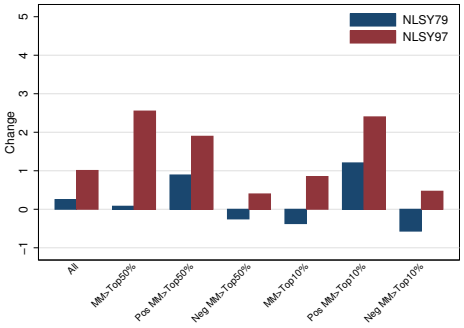
(d) Geographical Mobility: Change in Wages



(e) Occupational Mobility: Change in Weekly Hours Worked



(f) Geographical Mobility: Change in Weekly Hours Worked



Notes: See Section 3.2 for the construction of the skill mismatch measure. Positive (negative) mismatch occurs when a particular ability measure of a worker is above (below) the corresponding occupation requirement. Occupational mobility is defined as the change of occupation from one year to another accompanied by a job switch. Geographical mobility is conditional on an occupational switch occurring and the re-location of the individual to another commuting zone. The Y-axis shows the change of mismatch/wages/weekly hours worked from period t and $t+1$ for each cohort. The X-axis shows the different sub-samples: whole sample (All), Top 50% of the mismatch distribution, Top 50% of the positive mismatch distribution, Top 50% of the negative mismatch distribution,Top 10% of the mismatch distribution, Top 10% of the positive mismatch distribution, and Top 10% of the negative mismatch distribution. Wages are trimmed at the top and bottom 1%.

To validate our empirical analysis we present the results of our logit regression using two alternative mismatch measures (refer to Appendix D for the construction details). In particular, when we use a measure which we called *"AKM Skill Mismatch"*, after controlling for individual fixed effects we lose predictive power and we get an opposite sign between occupational mobility and skill mismatch; i.e. higher skill mismatch less occupational mobility in the economy, which is counterintuitive. In addition, when we use a skill mismatch measure based on "ideal wages" for each occupation, named *"Latent Wage Skill Mismatch"*, we completely lose significance and cannot suggest a causal relationship between skill mismatch and occupational mobility. With respect to geographical mobility, the effect of skill mismatch continues to be insignificant for the alternative measures, while for job separation the *latent wage* measure suggests a negative relationship; i.e. higher skill mismatch less job separation which contradicts the economic intuition established in the literature.

4 Model

In this section, we develop a discrete-time equilibrium search model (Mortensen and Pissarides, 1994) with multidimensional skills and job requirements. To this end, we extend the models of Lise et al. (2016) and Shephard and Sidibe (2019) to allow for multidimensional skill mismatch.

4.1 Environment

There is a total measure one of workers in the labor market. Workers are infinitely lived and risk neutral with common discount factor β. They can either be unemployed or employed in an occupation[21]. In addition, workers are heterogeneous in their multidimensional ability $\mathbf{a}$ which is continuous in a compact set $\mathbf{A} \subset \mathbb{R}^{\mathbf{3}}$, following a stationary distribution $\ell(\mathbf{a})$[22]. On the other hand, there is a measure n of jobs (either filled or unfilled) in the economy. Jobs can be characterized by their continuous requirements $\mathbf{r}$ in a compact set $\mathbf{R} \subset \mathbb{R}^3$. There is a

[21]In this model, we use "occupation" and "job" interchangeably. Therefore, each job change corresponds to an occupational switch. In doing so, we ignore within occupation job to job transitions.

[22]In the model, $\mathbf{a}$ is considered to be the worker's innate skills/abilities. We abstract from schooling choices. Including such choices in the manner of Shephard and Sidibe (2019) would likely amplifies the effects of skill mismatch.

fixed cross-sectional distribution of jobs $\gamma(\mathbf{r})$[23]. Finally, there is random search in the labor market. Hence, both employed and unemployed workers can search for any vacant job. In the baseline specification, we abstract from human capital accumulation process, later in the quantitative analysis, we extend the baseline model to investigate the role of on-the-job learning on sorting, skill mismatch and occupational mobility.

4.2 Unemployed Workers

Unemployed workers with ability $\mathbf{a}$ receive a flow utility $b(\mathbf{a})$ of non-employment activity, which include such things as leisure, home production, and unemployment benefits. In the next period, there is a probability ρ^u that they will meet with a vacant job with a distribution function $F^v(\mathbf{r})$.

Therefore, the value of being unemployed with ability $\mathbf{a}$ is given by

$$V^U(\mathbf{a}) = b(\mathbf{a}) + \beta \left[\rho^u \int_{\mathbf{r}'} \max \left\{ V^W(\mathbf{a}, \mathbf{r}'; \eta_0), V^U(\mathbf{a}) \right\} dF^v(\mathbf{r}') + (1 - \rho^u) V^U(\mathbf{a}) \right] \tag{6}$$

where $V^W(\mathbf{a}, \mathbf{r}; \eta_0)$ is the value of being employed in a $(\mathbf{r})$ job, and η_0 is a parameter to denote the initial worker's share of the match surplus.

4.3 Employed Workers

Employed workers with ability $\mathbf{a}$ and worker's share η in an $\mathbf{r}$ job earn a wage $w(\mathbf{a}, \mathbf{r}; \eta)$ which will be determined below. In the next period, there is an exogenous separation rate s. Otherwise, with probability ρ^e they meet with a vacant firm and receive an outside job offer[24], in which case they bargain wages via sequential auction between the competing firms in the spirit of Cahuc et al. (2006). The value of being employed can then be written as

$$V^W(\mathbf{a}, \mathbf{r}; \eta) = w(\mathbf{a}, \mathbf{r}; \eta) + \beta \left\{ sV^U(\mathbf{a}) + (1 - s) \left[\begin{array}{c} \rho^e \int_{\mathbf{r}'} \tilde{V}^W(\mathbf{a}, \mathbf{r}; \eta; \mathbf{r}') dF^v(\mathbf{r}') \\ +(1 - \rho^e) V^W(\mathbf{a}, \mathbf{r}; \eta) \end{array} \right] \right\} \tag{7}$$

[23]Long-run technological change would likely lead to significant changes in γ. For the sake of simplicity, we abstract from this possibility.

[24]In this model, only vacant firms are able to poach workers from another firm. Therefore, we consider only workers' mobility between jobs, but not job churning by the firms.

where

$$\tilde{V}^W(\mathbf{a},\mathbf{r};\eta;\mathbf{r}') = \begin{cases} V^W(\mathbf{a},\mathbf{r}';\eta^W_{move}) & \text{if } S(\mathbf{a},\mathbf{r}) < S(\mathbf{a},\mathbf{r}') \\ V^W(\mathbf{a},\mathbf{r};\eta^W_{stay}) & \text{if } V^W(\mathbf{a},\mathbf{r};\eta) - V^U(\mathbf{a}) \leq S(\mathbf{a},\mathbf{r}') \leq S(\mathbf{a},\mathbf{r}) \\ V^W(\mathbf{a},\mathbf{r};\eta) & \text{if } S(\mathbf{a},\mathbf{r}') < V^W(\mathbf{a},\mathbf{r};\eta) - V^U(\mathbf{a}) \end{cases} \tag{8}$$

is the value of employment with an outside offer from an $\mathbf{r}'$ job and $S(\mathbf{a},\mathbf{r})$ is the total match surplus. Intuitively, if the match surplus from the outside job $S(\mathbf{a},\mathbf{r}')$ (net of moving cost) is lower than the current worker's surplus, then there is no way the new job can provide higher surplus. So there will be no trade and the worker's value will stay the same. On the other hand, if $S(\mathbf{a},\mathbf{r}')$ is higher than the current worker's surplus, but lower than the current match surplus $S(\mathbf{a},\mathbf{r})$, then the two firms would compete until the worker earns the whole amount $S(\mathbf{a},\mathbf{r}')$ plus a fraction η_0 of the difference $(S(\mathbf{a},\mathbf{r}) - S(\mathbf{a},\mathbf{r}'))$. Finally, if $S(\mathbf{a},\mathbf{r}')$ is larger than $S(\mathbf{a},\mathbf{r})$, then the worker would move to the new job with worker's surplus given by $S(\mathbf{a},\mathbf{r})$ plus a fraction η_0 of the difference $(S(\mathbf{a},\mathbf{r}') - S(\mathbf{a},\mathbf{r}))$.

It can be shown that the new worker's shares of the last two cases are given by

$$\eta^W_{stay} = \eta_0 + (1-\eta_0)\frac{S(\mathbf{a},\mathbf{r}')}{S(\mathbf{a},\mathbf{r})} \tag{9}$$

$$\eta^W_{move} = \eta_0 + (1-\eta_0)\frac{S(\mathbf{a},\mathbf{r})}{S(\mathbf{a},\mathbf{r}')} \tag{10}$$

4.4 Matched Firm

If matched, the worker-job pair jointly earns a product $\phi(\mathbf{a},\mathbf{r})$. The firm pays the worker a wage $w(\mathbf{a},\mathbf{r};\eta)$. After exogenous separation, the job becomes unfilled. Otherwise, there could be endogenous separation when the employee quits the job for a better offer. Let $V^V(\mathbf{r})$ be the value of an unfilled job. The value of a productive matched firm is then given by

$$\begin{aligned} \Pi(\mathbf{a},\mathbf{r};\eta) = \quad & \phi(\mathbf{a},\mathbf{r}) - w(\mathbf{a},\mathbf{r};\eta) \\ + \quad & \beta(1-s)\left[\rho^e \int_{\mathbf{r}'} \tilde{\Pi}(\mathbf{a},\mathbf{r};\eta;\mathbf{r}')dF^v(\mathbf{r}') + (1-\rho^e)\Pi(\mathbf{a},\mathbf{r};\eta)\right] + \beta s V^V(\mathbf{r}) \end{aligned} \tag{11}$$

where $\tilde{\Pi}(\mathbf{a}, \mathbf{r}; \eta; \mathbf{r}')$ is the value of the firm when the employee receives an outside offer from a $(\mathbf{r}')$ job:

$$\tilde{\Pi}(\mathbf{a}, \mathbf{r}; \eta; \mathbf{r}') = \begin{cases} V^V(\mathbf{r}) & \text{if } S(\mathbf{a}, \mathbf{r}) < S(\mathbf{a}, \mathbf{r}') \\ \Pi(\mathbf{a}, \mathbf{r}; \eta^W_{stay}) & \text{if } V^W(\mathbf{a}, \mathbf{r}; \eta) - V^U(\mathbf{a}) \leq S(\mathbf{a}, \mathbf{r}') \leq S(\mathbf{a}, \mathbf{r}) \\ \Pi(\mathbf{a}, \mathbf{r}; \eta) & \text{if } S(\mathbf{a}, \mathbf{r}') < V^W(\mathbf{a}, \mathbf{r}; \eta) - V^U(\mathbf{a}) \end{cases} \tag{12}$$

Similar to the case of the employed worker, there are three cases depending on the level of surplus from the outside job $S(\mathbf{a}, \mathbf{r}')$ net of moving cost. Note that, for example, in the case when the employee leaves the firm for a better job, the firm becomes unfilled with the value $V^V(\mathbf{r})$.

4.5 Firm Entry

There is a flow cost c of maintaining a vacancy. With probability q^u, the vacant firm meets with an unemployed worker. There is a probability q^e of meeting an employed worker. Let $F^u(\mathbf{a})$ and $F^m(\mathbf{a}, \mathbf{r})$ be the distribution function of unemployed and employed workers respectively across ability and job requirement. The value of a vacancy with skill requirement $\mathbf{r}$ is hence given by

$$\begin{aligned} V^V(\mathbf{r}) = & -c + \beta q^u \int_{\mathbf{a}} \max\left\{\Pi(\mathbf{a}, \mathbf{r}; \eta_0), V^V(\mathbf{r})\right\} dF^u(\mathbf{a}) \\ & + \beta q^e \int_{\mathbf{r}'} \int_{\mathbf{a}} \max\left\{\hat{\Pi}(\mathbf{a}, \mathbf{r}; \mathbf{r}'), V^V(\mathbf{r})\right\} dF^m(\mathbf{a}, \mathbf{r}') + \beta(1 - q^u - q^e) V^V(\mathbf{r}) \end{aligned} \tag{13}$$

where

$$\hat{\Pi}(\mathbf{a}, \mathbf{r}; \mathbf{r}') = \begin{cases} \Pi(\mathbf{a}, \mathbf{r}; \eta^F_{move}) & \text{if } S(\ \mathbf{a}, \mathbf{r}') < S(\mathbf{a}, \mathbf{r}) \\ V^V(\mathbf{r}) & \text{if } S(\mathbf{a}, \mathbf{r}) \leq S(\mathbf{a}, \mathbf{r}') \end{cases} \tag{14}$$

is the value of the firm when meeting with an employed worker with attribute $(\mathbf{a}, \mathbf{r}')$. Note that the current match surplus of the employed worker $S(\mathbf{a}, \mathbf{r}')$ has to be lower than the potential match surplus in order for the worker to accept the new job. In this case, the worker moves to match with the vacant job with worker's share given by

$$\eta^F_{move} = \eta_0 + (1 - \eta_0) \frac{S(\mathbf{a}, \mathbf{r}')}{S(\mathbf{a}, \mathbf{r})} \tag{15}$$

Otherwise, the job stays unfilled.

Following Lise et al. (2016) and Shephard and Sidibe (2019), the free entry condition is such that the lowest value of vacancy across all job requirement is zero:

$$\min_{\mathbf{r}} V^V(\mathbf{r}) = 0 \tag{16}$$

4.6 Matching, Surplus and Wage Bargaining

Let $\{u, m, v\}$ be the measures of unemployed workers, matches, and job vacancies respectively. We assume a standard constant-returns-to-scale matching function $M(n_s, v) = An_s^{\alpha} v^{1-\alpha}$, where $n_s = u + \xi m$ is the effective number of search workers. Then the aggregate labor market tightness is given by

$$\theta = \frac{v}{n_s} = \frac{v}{u + \xi m} \tag{17}$$

where ξ is the relative matching efficiency of the employed workers which may include such things as the relative time and effort of job search. The meeting rates between unemployed workers and vacant firms are then defined respectively as

$$\rho^u = \frac{M(n_s, v)}{n_s} = A\theta^{1-\alpha} \tag{18}$$

$$q^u = \frac{M(n_s, v)}{v} = A\theta^{-\alpha} \tag{19}$$

Hence, the meeting rates between employed workers and vacant firms are simply

$$\rho^e = \xi \rho^u \tag{20}$$

$$q^e = \xi q^u \tag{21}$$

The total surplus from matching is the difference between the sum of matched values and the value of unemployment:

$$
\begin{aligned}
S(\mathbf{a},\mathbf{r}) &= V^W(\mathbf{a},\mathbf{r};\eta) + \Pi(\mathbf{a},\mathbf{r};\eta) - V^U(\mathbf{a}) - V^V(\mathbf{r}) \\
&= \phi(\mathbf{a},\mathbf{r}) - b(\mathbf{a}) + c + \beta(1-s)\left[\rho^e \int_{\mathbf{r}'} \tilde{S}(\ \mathbf{a},\mathbf{r};\mathbf{r}',l')dF^v(\mathbf{r}') + (1-\rho^e)S(\mathbf{a},\mathbf{r})\right] \\
&- \beta\rho^u \int_{\mathbf{r}'} \max\left\{\eta_0 S(\ \mathbf{a},\mathbf{r}'),0\right\} dF^v(\mathbf{r}') - \beta q^u \int_{\mathbf{a}'} (1-\eta_0)\max\left\{S(\mathbf{a}',\mathbf{r}),0\right\} dF^u(\mathbf{a}') \\
&- \beta q^e \int_{\mathbf{r}'}\int_{\mathbf{a}} (1-\eta_0)\max\left\{S(\mathbf{a}',\mathbf{r}) - S(\mathbf{a}',\mathbf{r}'),0\right\} dF^m(\mathbf{a}',\mathbf{r}') \qquad (22)
\end{aligned}
$$

which is independent of the worker's share and where

$$
\tilde{S}(\mathbf{a},\mathbf{r};\mathbf{r}') = \begin{cases} \eta_0 S(\mathbf{a},\mathbf{r}') + (1-\eta_0)S(\mathbf{a},\mathbf{r}) & \text{if } S(\mathbf{a},\mathbf{r}) \leq S(\mathbf{a},\mathbf{r}') \\ S(\mathbf{a},\mathbf{r}) & \text{if } S(\mathbf{a},\mathbf{r}') < S(\mathbf{a},\mathbf{r}) \end{cases} \qquad (23)
$$

Wages are pinned down by the worker's share of the total surplus. Specifically, for any effective worker's share $\eta \in [0,1]$, the wage is implicitly determined by the Nash sharing rules:

$$
V^W(\mathbf{a},\mathbf{r};\eta) - V^U(\mathbf{a}) = \eta S(\mathbf{a},\mathbf{r}) \qquad (24)
$$

By substituting the value of employed and unemployed workers, the wage function can be written as

$$
\begin{aligned}
w(\mathbf{a},\mathbf{r};\eta) = \eta\phi(\mathbf{a},\mathbf{r}) + (1-\eta)b(\mathbf{a}) + \beta(1-s)\rho^e \int_{\mathbf{r}'} \begin{bmatrix} \eta\tilde{S}(\mathbf{a},\mathbf{r};\mathbf{r}') \\ -(\tilde{V}^W(\mathbf{a},\mathbf{r};\eta;\mathbf{r}') - V^U(\mathbf{a})) \end{bmatrix} dF^v(\mathbf{r}') \\
+ (1-\eta)\beta\rho^u \int_{\mathbf{r}'} \max\left\{\eta_0 S(\mathbf{a},\mathbf{r}'),0\right\} dF^v(\mathbf{r}') - \eta(1-\beta)V^V(\mathbf{r}) \qquad (25)
\end{aligned}
$$

4.7 Stationary Flow Equation and Equilibrium

Let $m(\mathbf{a},\mathbf{r})$ be the number of matches. Then since workers can either be employed or unemployed, we must have for each $\mathbf{a}$,

$$
u(\mathbf{a}) + \int_{\mathbf{r}} m(\mathbf{a},\mathbf{r})d\mathbf{r} = l(\mathbf{a}) \qquad (26)
$$

Similarly, since jobs can either be filled or unfilled, we have

$$v(\mathbf{r}) + \int_{\mathbf{a}} m(\mathbf{a}, \mathbf{r}) d\mathbf{a} = n(\mathbf{r}) \tag{27}$$

where $n(\mathbf{r}) = n\gamma(\mathbf{r})$ is the total number of $\mathbf{r}$ jobs. In equilibrium, the meeting density function of the unemployed workers, vacancies, and matches are respectively given by

$$f^u(\mathbf{a}) = \frac{u(\mathbf{a})}{n_s} \tag{28}$$

$$f^v(\mathbf{r}) = \frac{v(\mathbf{r})}{v} \tag{29}$$

$$f^m(\mathbf{a}, \mathbf{r}) = \frac{m(\mathbf{a}, \mathbf{r})}{n_s} \tag{30}$$

Finally, in a steady state, we must have that the inflows of matches equals to the outflows. Hence, whenever $S(\mathbf{a}, \mathbf{r}) \geq 0$, we have

$$\left[s + (1-s)\rho^e \int\limits_{S(\mathbf{a},\mathbf{r}) \leq S(\mathbf{a},\mathbf{r}')} f^v(\mathbf{r}') d\mathbf{r}' \right] m(\mathbf{a}, \mathbf{r}) = \left[\rho^u u(\mathbf{a}) + \rho^e \int\limits_{S(\mathbf{a},\mathbf{r}') \leq S(\mathbf{a},\mathbf{r})} m(\mathbf{a}, \mathbf{r}') d\mathbf{r}' \right] f^v(\mathbf{r}) \tag{31}$$

Then, the inflow of matches includes those unemployed workers with ability $\mathbf{a}$, and those employed with lower enough match surplus to meet with the $\mathbf{r}$ job. On the other hand, the outflow comprises exogenous and endogenous separations arising from on the job search. We are now ready to define an equilibrium in the model.

Definition 1. *A stationary equilibrium is a set of match surplus $S(\mathbf{a}, \mathbf{r})$, distributions of workers and jobs $\{u(\mathbf{a}), m(\mathbf{a}, \mathbf{r}), v(\mathbf{r})\}$, and market tightness θ, such that given the distributions of skills and job requirements $\{l(\mathbf{a}), \gamma(\mathbf{r})\}$*

(i) Match surplus satisfies (22);

(ii) Distributions of workers and jobs satisfy clearing conditions (26) and (27), and the stationary flow equation (31); and

(iii) Market tightness satisfies the free entry condition (16).

4.8 Skill Mismatch and Occupational Mobility Measures

To study skill mismatch and occupational mobility, we need to define their measures in the model. First, following the empirical measure, the skill mismatch for each employed worker is given by

$$mm(\mathbf{a}, \mathbf{r}) = \sum_i \omega_i \left| a_i - r_i \right| \tag{32}$$

The aggregate skill mismatch is then the weighted average:

$$MM = \frac{\int_{\mathbf{a},\mathbf{r}} mm(\mathbf{a}, \mathbf{r}) m(\mathbf{a}, \mathbf{r}) d(\mathbf{a}, \mathbf{r})}{\int_{\mathbf{a},\mathbf{r}} m(\mathbf{a}, \mathbf{r}) d(\mathbf{a}, \mathbf{r})} \tag{33}$$

For each $(\mathbf{a}, \mathbf{r})$-type employed worker, the probability of switching jobs (and hence occupations) is given by

$$om(\mathbf{a}, \mathbf{r}) = (1 - s)\rho^e \int\limits_{S(\mathbf{a},\mathbf{r}) \leq S(\mathbf{a},\mathbf{r}')} f^v(\mathbf{r}') d\mathbf{r}' \tag{34}$$

Hence, the aggregate occupational mobility rate is then

$$OM = \frac{\int_{\mathbf{a},\mathbf{r}} om(\mathbf{a}, \mathbf{r}) m(\mathbf{a}, \mathbf{r}) d(\mathbf{a}, \mathbf{r})}{\int_{\mathbf{a},\mathbf{r}} m(\mathbf{a}, \mathbf{r}) d(\mathbf{a}, \mathbf{r})} \tag{35}$$

In this specification, if skill mismatch hurts production, then there would be a positive relationship between skill mismatch and occupational mobility. To see that, first note from the construction and surplus equation (22) that the match surplus $S(\mathbf{a}, \mathbf{r})$ is increasing in the match product $\phi(\mathbf{a}, \mathbf{r})$. Now if $\phi(\mathbf{a}, \mathbf{r})$ is decreasing in the skill match $mm(\mathbf{a}, \mathbf{r})$ as in the empirical results, then the probability that an employed worker finds a better job (in the sense that $S(\mathbf{a}, \mathbf{r}) \leq S(\mathbf{a}, \mathbf{r}')$) is then increasing in $mm(\mathbf{a}, \mathbf{r})$. It follows that the occupational mobility $om(\mathbf{a}, \mathbf{r})$ is increasing with the skill mismatch $mm(\mathbf{a}, \mathbf{r})$.

Result 1. *Suppose, other things equal, $\phi(\mathbf{a}, \mathbf{r})$ is decreasing in $mm(\mathbf{a}, \mathbf{r})$. Then individual's occupational mobility is increasing in the skill mismatch.*

Table 4: **Baseline Calibration**

Parameter	Meaning	Value	Target/source
		Preset parameters	
b	Flow utility of unemployment	0.4	Shimer (2005)
α	Matching elasticity	0.5	Petrongolo and Pissarides (2001)
η_0	Worker's bargaining power	0.5	Hosios condition
c	Cost of maintaining vacancy	0.17	Fujita and Ramey (2012)
β	Discount factor	0.9967	4% annual discount rate
		Calibrated parameters	
A	Matching efficiency	0.764	Monthly job finding rate (14.95%)
ξ	Relative search intensity of the employed	0.186	Monthly occupational mobility rate (0.91%)
s	Exogenous separation rate	0.00972	Unemployment rate (6.05%)
z	Aggregate productivity	0.5372	Average labor productivity (1.00)

5 Quantitative Analysis

In this section, we calibrate the model to the US labor market[25]. We then explore the relationship between skill mismatch and occupational mobility in the model and the consequence of multidimensionality of skills. The model is then extended to include on-the-job learning to study the role of human capital accumulation on skill mismatch and occupational mobility. Finally, we investigate the impacts of aggregate productivity growth and unemployment benefit on skill mismatch and occupational mobility.

5.1 Calibration and Specifications

The set of abilities and job requirements are taken to be $[0,1]^3$, consistent with the normalization in the empirical data. The distribution of abilities $\ell(\mathbf{a})$ and requirements $\gamma(\mathbf{r})$ are then derived from the cross-sectional sample in the NLSY79 data.

There is an aggregate productivity factor z. The production function is then taken to be

$$\phi(\mathbf{a},\mathbf{r}) = z\tilde{\phi}(\mathbf{a},\mathbf{r}) \tag{36}$$

with

$$\log\tilde{\phi}(\mathbf{a},\mathbf{r}) = \sum_{i=1}^{3}\lambda_i^a a_i + \sum_{i=1}^{3}\lambda_i^r r_i + \sum_{i=1}^{3}\lambda_i^{mm} mm_i \tag{37}$$

where $mm_i = |a_i - r_i|$ is the ith component mismatch. The parameters $\{\lambda_i^a, \lambda_i^r, \lambda_i^{mm}\}_{i=1}^3$ are

[25]Details of the computational algorithm are in Appendix C.

recovered from the wage regressions using the NLSY79 (See Table B.4). It can be shown that the resulting wage function produces regression coefficients reasonably close to the empirical results.

We set some of the parameters to the standard values in the literature. To avoid time aggregation issues, one period of the model is taken to be one month. The discount factor β is then 0.9967, which is consistent with an annual discount rate of 4%. Standard in the literature, the bargaining power of the worker, η_0, is assumed to be 0.5. We assume Hosios condition, which implies $\alpha = \eta_0 = 0.5$. The flow utility of unemployment is 0.4, following Shimer (2005). Finally, the vacancy cost c is taken to be 0.17, following Fujita and Ramey (2012).

The rest of the parameters is jointly calibrated to match moments in the NLSY79 data. First, the parameter of matching efficiency, A, is identified by matching the monthly job finding rate in the data, which is found to be about 15%. Also, the relative search intensity of the employed workers ξ is chosen such that the implied monthly occupational mobility rate is 0.91% as in the data. The exogenous separation rate is taken to match the unemployment rate 6.05% in the NLSY79 sample. Finally, the aggregate productivity factor z is determined by normalizing the labor productivity to be one.

To evaluate the effect of multidimensionality on the relationship between mismatch and mobility, we also calibrate a one-dimensional version of the model. To do this, we use the one-dimensional skill and job requirement as defined in Section D.2. We then target the same set of moments as above. The calibration parameters are in Table E.1.

Table 4 summarizes the value of parameters in the baseline calibration. Figure A.1 in Appendix A shows the resulting skill mismatch distribution. Column (1) of Table 5 shows the aggregate labor market moments in the model. We measure income inequality by the Gini coefficient both for all workers ($Gini$) and for only the employed workers ($Gini_w$). Finally, the welfare function is defined by

$$Welfare = \int_{\mathbf{a},\mathbf{r}} \phi(\mathbf{a},\mathbf{r}) m(\mathbf{a},\mathbf{r}) d(\mathbf{a},\mathbf{r}) + \int_{\mathbf{a}} b(\mathbf{a}) u(\mathbf{a})\, d\mathbf{a} - cv \tag{38}$$

Table 5: **Aggregate Labor Market Moments**

Moment	(1) Baseline	(2) No mobility		(3) Multidimensional sorting	
Job finding rate	14.96%	17.65%	(2.68%)	14.96%	
Occupational mobility rate	0.90%	0.00%	(−0.90%)	0.44%	(−0.46%)
Unemployment rate	6.05%	5.22%	(−0.83%)	6.05%	
Average skill mismatch	1.61	1.78	(11.00%)	0.58	(−63.88%)
Number of jobs	0.96	0.96	(0.01%)	0.96	
Number of vacancies	0.02	0.01	(−38.16%)	0.02	
Labor market tightness	0.09	0.25	(178.65%)	0.09	
Average labor productivity	1.00	1.00	(−0.28%)	1.01	(0.90%)
GDP	0.94	0.95	(0.59%)	0.95	(0.90%)
$Gini$	0.13	0.13	(0.42%)	0.14	(1.53%)
$Gini_w$	0.13	0.13	(1.23%)	0.13	(1.52%)
$Welfare$	0.96	0.96	(0.38%)	0.97	(0.88%)

Notes: $Gini$ refers to the Gini coefficient for all workers whereas $Gini_w$ refers to that for only the employed workers. The welfare function is defined by (38). The numbers in parentheses represents the percentage point change (for job finding, occupational mobility, and unemployment rates) or percentage change (the rest) compared to the baseline.

5.2 Skill Mismatch and Occupational Mobility

How would the model predict the relationship between skill mismatch and occupational mobility? To answer this question, we perform a regression analysis on the occupational mobility and skill mismatch with 1 million simulated observations. Table 6 shows the linear regression result. We can see that the model predicts a positive relationship between skill mismatch and occupational mobility, consistent with the theoretical argument in the previous section and our empirical findings. Quantitatively, one standard deviation increase in the skill mismatch is associated with 0.7% increase in the monthly occupational mobility rate, closely resembling the results in the data.

What is the aggregate impact if there is no occupational mobility? The last column in Table 5 shows the aggregate labor market statistics when there is no occupational mobility (i.e. $\xi = 0$). We can see that when the job-to-job transition is not allowed, the average skill mismatch would increase by about 10%. This is because occupational mobility would in general improve skill mismatch. Moreover, while the number of jobs (filled or unfilled) stay roughly the same, the labor market tightness increases significantly. This is due to the fact that as employed workers are not allowed to move across jobs, the number of search workers drop significantly. This leads to a higher job finding rate and a lower unemployment rate. Moreover, while the average productivity of workers decreases slightly, the aggregate

Table 6: **Regression Results: Model vs. Data**

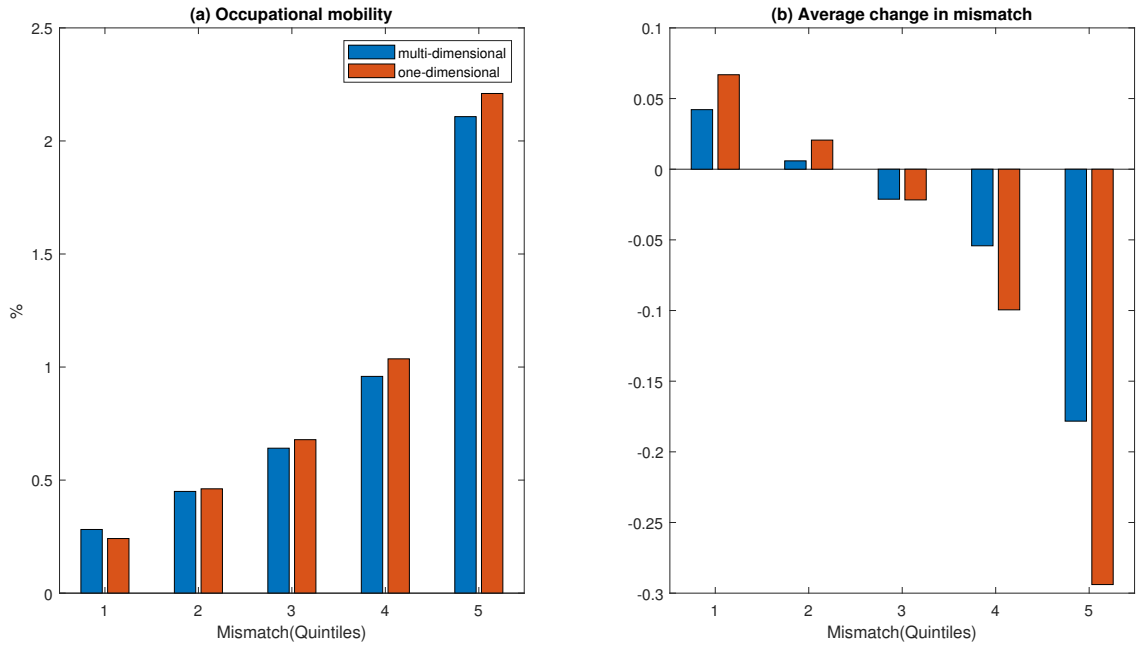
Variable:	*Occupational mobility (monthly)*	
	Model	Data
Mismatch	0.00717***	0.00728***
	(5.75e-06)	(9.33e-04)
Constant	-0.00256***	1.321***
	(1.09e-05)	(0.0210)
R^2	0.609	0.101
Observations	1,000,000	131,130

Notes: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p <0.1.

output (GDP) increases by half a percent, primarily due to two opposing effects: While the increased mismatch hurts the output of the matches, employment in the economy is boosted more substantially. The income inequality, as measured by the Gini coefficient, increases by 0.4% for all individuals and more than 1% for the employed workers. Lastly, there is only a slight improvement of welfare, mainly due to the increased output.

Panel (a) of Figure 5 shows the occupational mobility in each of mismatch quintile. Again we observe the positive relationship. Note, however, that the relationship is non-linear: those with high skill mismatch are associated with much higher occupational mobility. Shown in the same panel is the mobility rates in the one-dimensional model. We can see that while both models have predicted a similar relationship between skill mismatch and occupational mobility, the relationship in the one-dimensional model is slightly steeper. It is much more pronounced if we look at the average change in mismatch for those occupation switchers, shown in panel (b). Compared to the multidimensional model, the one-dimensional one predicts a much higher improvement in skill mismatch when highly mismatched workers move to a different occupation. It is because absent the multidimensional correlations between skills, sorting becomes much easier with mobility, thus the large improvement in mismatch. As we will see below, perfect sorting (in the sense that mismatch becomes zero for all workers) is not possible when there are multidimensional skills due to their imperfect correlations. Therefore, using a one-dimensional model tends to overstate the relationship between mismatch and mobility, and the improvement of skill mismatch by occupational mobility. Hence, policy analysis using a one-dimensional model are likely to be less reliable quantitatively.

Figure 5: **Skill Mismatch and Occupational Mobility**



5.3 Multidimensional Sorting and Cost of Skill Mismatch

Due to the output loss by skill mismatch, the model naturally predicts some multidimensional sorting between worker skill and job requirement[26]. Figure 6b shows the joint employment distributions for each skill component in the data and in the baseline model. In the ideal case with perfect sorting and matching, we would expect that employment lies only on the diagonal line. We can see that in the baseline case, in general, there is some level of assortative matching in the economy, with the math and verbal components showing stronger level of sorting than the social component. Sorting in the data appears to be noisier than in the model but has similar correlation between skill and requirement. There are two reasons for the imperfect assortative matching in the model. First, there is the skill mismatch due to search frictions. Individual worker may not be able to find a best match job due to random matching. Second, in the empirical data, there are imperfect correlations between skill components for both workers and jobs.

To investigate the cost of skill mismatch due to search frictions, we consider the sorted em-

[26]Lindenlaub and Postel-Vinay (2020*a*) and Lindenlaub and Postel-Vinay (2020*b*) show the importance of multidimensional heterogeneity and the worker-job characteristics that impact worker-job surplus to study the sorting patterns, mismatch, and workers' mobility choices in the labor market.

ployment distribution that yields the lowest average skill mismatch, while keeping individual skill and job requirement distributions, and the unemployed workers unchanged[27]. To this end, the social planner reallocates the employed workers to the filled jobs which gives the lowest skill mismatch. Again due to the imperfect correlation of skills and requirements, such allocation would not entail a zero skill mismatch. Figure 6c shows the sorted employment distributions. In general, employment now aligns much closer to the diagonal line of perfect assortative matching. The average skill mismatch now measures 0.58 representing a 64% reduction compared to the baseline.

What is the aggregate impact of multidimensional sorting of workers? The third column of Table 5 shows the aggregate labor market statistics under multidimensional sorting. First, the occupational mobility rate reduces by half to 0.44%. This is because in the sorted employment distribution, most employed workers are already matched to the best job available. The remaining occupational mobility represents the flow to the unfilled vacancies in the market. Also, due to the better skill match, there is an about 1% boost in the average labor productivity and GDP. We also observe a similar increase in the total welfare as well. We therefore conclude that the cost of skill mismatch due to search frictions is about 1% of total output and welfare. Finally, income inequality in the economy measured by the Gini coefficient rises by about 1.5%. The increase in inequality is due to the fact that now the better jobs (in the sense that the job requirements are higher) are assigned to the more able workers.

We conclude that skill mismatch due to search frictions accounts for about two third of the total skill mismatch, while the rest is due to the imperfect correlation between skills. Also, the skill mismatch due to search frictions costs about 1% of the aggregate output and welfare.

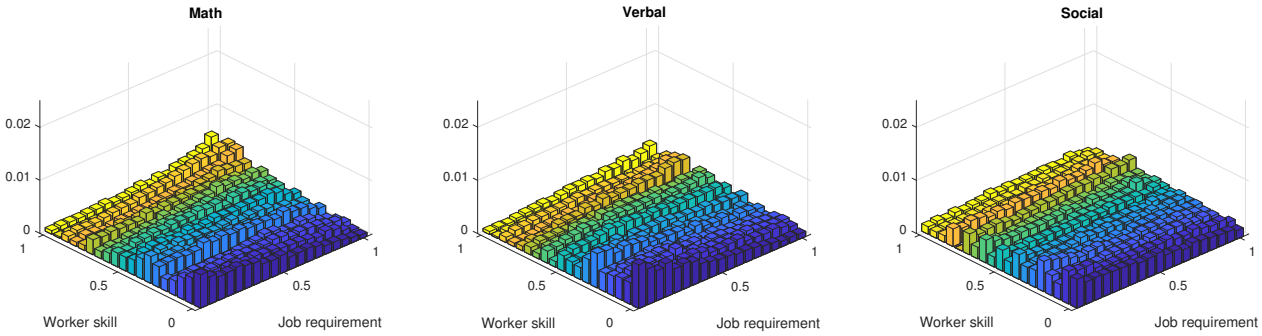
5.4 Human Capital Accumulation

In the baseline specification of the model, we abstract from human capital accumulation reflecting the on-the-job learning process that can be crucial to occupational mobility. To investigate the effects of human capital accumulation on skill mismatch and occupational mobility, we now extend the model to include on-the-job learning while employed.

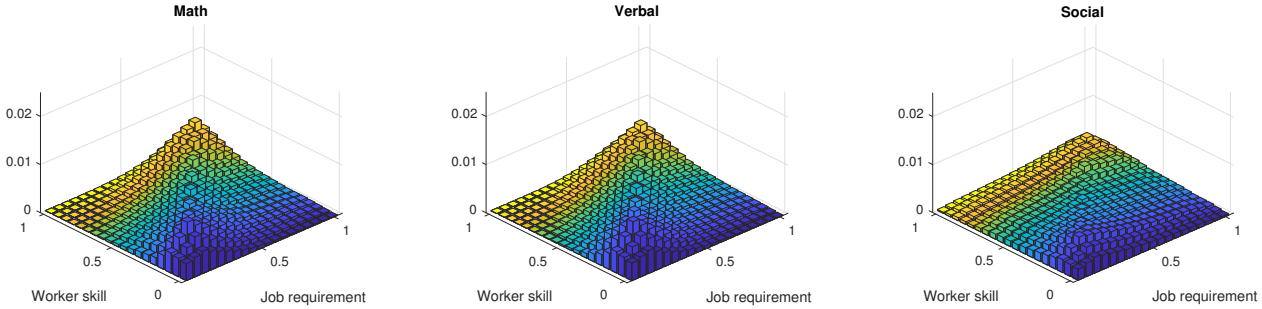
[27]To do this, we first compute the distribution of skills and requirements of employed workers and filled jobs. Then for a given permutation of workers, we assign each worker to the best job that matches the skills of the worker. If it is not available, we match the worker to the second best job, and so on. We choose the permutation that gives the lowest aggregate skill mismatch.

Figure 6: **Sorting between workers and jobs**

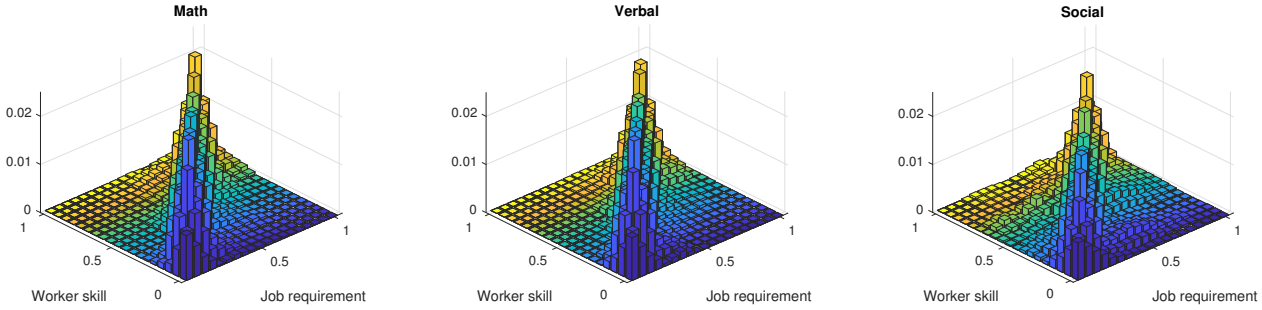
(a) Data



(b) Baseline



(c) Multidimensional sorting



In each period, there is a rate of learning ξ such that a worker with skill $\mathbf{a}$ working in an $\mathbf{r}$ job would acquire skill $\tilde{\mathbf{a}}(\mathbf{a},\mathbf{r})$ in the next period, given that the worker is not separating from the job. Hence, the value of being employed is now given by

$$V^W(\mathbf{a},\mathbf{r};\eta) = w(\mathbf{a},\mathbf{r};\eta) + \beta\left\{sV^U(\mathbf{a}) + (1-s)\left[\begin{array}{c}\rho^e \int_{\mathbf{r}'} \tilde{V}^W(\mathbf{a},\mathbf{r};\eta;\mathbf{r}')\,dF^v(\mathbf{r}') \\ +(1-\rho^e)\left[\xi V^W(\tilde{\mathbf{a}}(\mathbf{a},\mathbf{r}),\mathbf{r};\eta) + (1-\xi)V^W(\mathbf{a},\mathbf{r};\eta)\right]\end{array}\right]\right\} \tag{39}$$

The on-the-job learning function $\tilde{\mathbf{a}}(\mathbf{a},\mathbf{r})$ takes the form that each component of skills becomes closer to the respective job requirement component by an increment of λ. i.e. for each $i = 1,2,3$,

$$\tilde{a}_i = \begin{cases} a_i + \lambda & \text{if } a_i \leq r_i - \lambda \\ a_i - \lambda & \text{if } a_i \geq r_i + \lambda \\ a_i & \text{otherwise} \end{cases}$$

Quantitatively, we set $\lambda = 0.1$. Hence, there is skill accumulation if the worker is sufficiently underqualified and skill depreciation if the worker is sufficiently overqualified in each skill dimension. With the additional inflow and outflow of employment, the steady state employment is now defined by

$$\left[s + (1-s)\left(\rho^e \int_{S(\mathbf{a},\mathbf{r})\leq S(\mathbf{a},\mathbf{r}')} f^v(\mathbf{r}')\,d\mathbf{r}' + (1-\rho^e)\xi\right)\right] m(\mathbf{a},\mathbf{r})$$
$$= \left[\rho^u u(\mathbf{a}) + \rho^e \int_{S(\mathbf{a},\mathbf{r}')\leq S(\mathbf{a},\mathbf{r})} m(\mathbf{a},\mathbf{r}')\,d\mathbf{r}'\right] f^v(\mathbf{r}) + (1-s)(1-\rho^e)\xi \int_{(\mathbf{a}',\mathbf{r}):\tilde{\mathbf{a}}(\mathbf{a}',\mathbf{r}')=\mathbf{a}} m(\mathbf{a}',\mathbf{r})\,d(\mathbf{a}',\mathbf{r}) \tag{40}$$

Figure 7 shows the sorting of workers and jobs when $\xi = 0.1\%$, 0.5%, and 1%, respectively. The aggregate labor market statistics from $\xi = 0.1\%$ to $\xi = 1\%$ are given in Table 5. As the rate of on-the-job-learning increases, workers are better matched in each skill dimension. This is the direct consequence of skill learning. However, this translates to only 8% drop in the average skill mismatch. This is because in the presence of on-the-job learning, unemployed workers are less fastidious in accepting a job with different job requirements. As a result, there is significant decrease in the unemployment rate. For instance, the case when $\xi = 1\%$ entails a more than 4 percentage point drop in unemployment compared to the baseline.

Table 7: **Aggregate Labor Market Moments under different rates of learning**

	ξ										
Moment	0.0%	0.1%	0.2%	0.3%	0.4%	0.5%	0.6%	0.7%	0.8%	0.9%	1.0%
Job finding rate	14.96%	15.05%	15.07%	15.12%	15.15%	14.61%	14.00%	13.57%	13.70%	12.67%	11.15%
Occupational mobility rate	0.90%	0.88%	0.86%	0.83%	0.81%	0.76%	0.70%	0.65%	0.59%	0.54%	0.47%
Unemployment rate	6.05%	6.00%	5.96%	5.88%	5.77%	5.60%	5.29%	4.80%	3.88%	2.97%	1.77%
Average skill mismatch	1.61	1.57	1.54	1.50	1.46	1.46	1.46	1.47	1.46	1.48	1.48
Number of jobs	0.96	0.96	0.96	0.96	0.96	0.96	0.97	0.97	0.98	0.99	1.00
Number of vacancies	0.02	0.02	0.02	0.02	0.02	0.02	0.03	0.03	0.04	0.05	0.06
Labor market tightness	0.09	0.09	0.09	0.09	0.09	0.09	0.11	0.13	0.16	0.22	0.31
Average labor productivity	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.99
GDP	0.94	0.94	0.94	0.94	0.94	0.94	0.95	0.95	0.96	0.96	0.98
$Gini$	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.12	0.12	0.11
$Gini_w$	0.13	0.13	0.13	0.13	0.13	0.12	0.12	0.12	0.12	0.11	0.11
$Welfare$	0.96	0.96	0.96	0.96	0.96	0.96	0.97	0.97	0.97	0.98	0.99

Notes: $Gini$ refers to the Gini coefficient for all workers whereas $Gini_w$ refers to that for only the employed workers. The welfare function is defined by (38).

Therefore, the number of workers with less aligned skills with their job also rises.

The human capital accumulation process also disincentivizes occupational mobility. This is intuitively: workers no longer have to find a better match by moving to a different job. Workers *become* better matched as they stay in their own job. In fact, the occupational mobility rate almost cut in half from 0.9% to 0.47% as we move from $\xi = 0\%$ to $\xi = 1\%$.

In general, any worker-job pair now produces higher surplus through the expectation of on-the-job learning. This encourages vacancy creation in the market. As a result, we see that there is an increase in the number of jobs, the number of vacancies, and the labor market tightness.

Finally, as we move from the baseline to $\xi = 1\%$, while the average labor productivity drops by less than 1% due to the increased number of bad matches, the aggregate output still rises by 4% because of the significantly surge in employment. There is also a 15% drop in income inequality and 3% improvement in the total welfare.

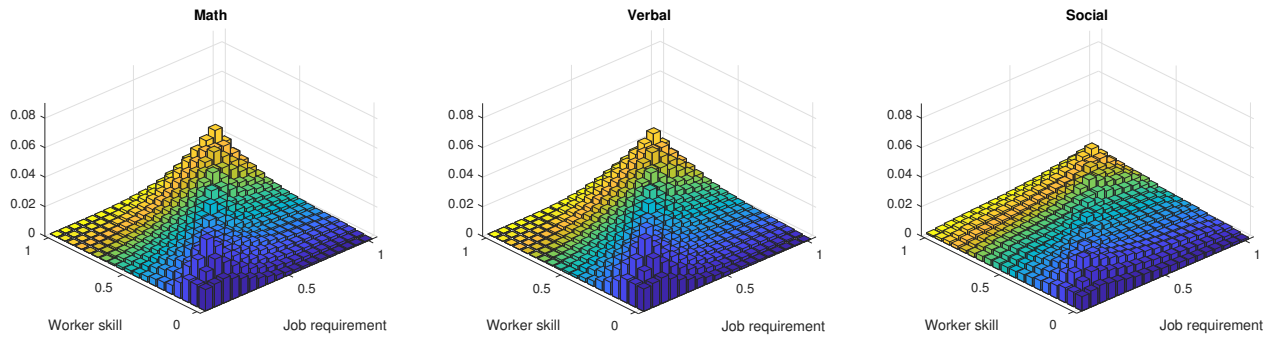
5.5 Aggregate Productivity Growth

How would aggregate productivity growth affect mismatch and mobility? To answer this, we consider an increase of the aggregate productivity factor z. In this case, z increases from 0.537 to 0.645, roughly equal to a 20% increase.

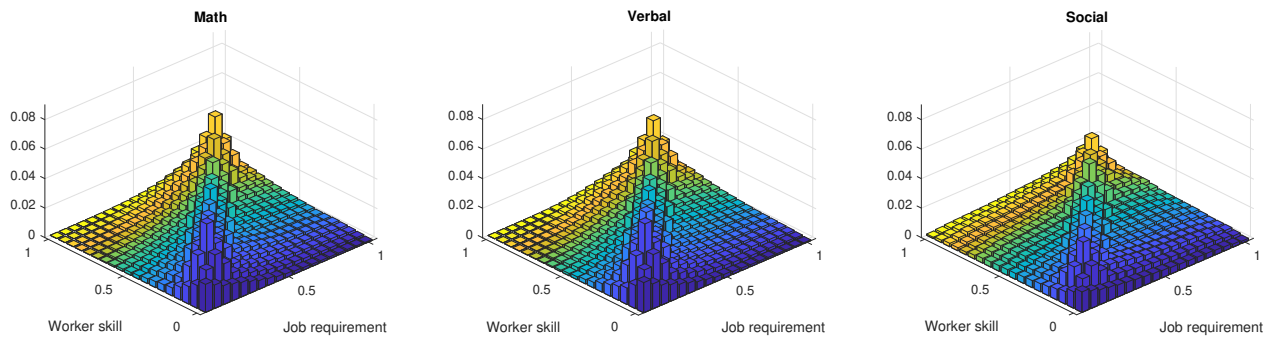
Figure 8 shows the effects of increasing aggregate productivity on aggregate skill mismatch, occupational mobility, unemployment rate and GDP. There exist two opposing effects on skill mismatch and occupational mobility when we change the aggregate productivity. First, as labor becomes more productive then there is a direct effect on occupational mobility

Figure 7: **Sorting under different rates of learning**

(a) $\xi = 0.1\%$



(b) $\xi = 0.5\%$



(c) $\xi = 1.0\%$

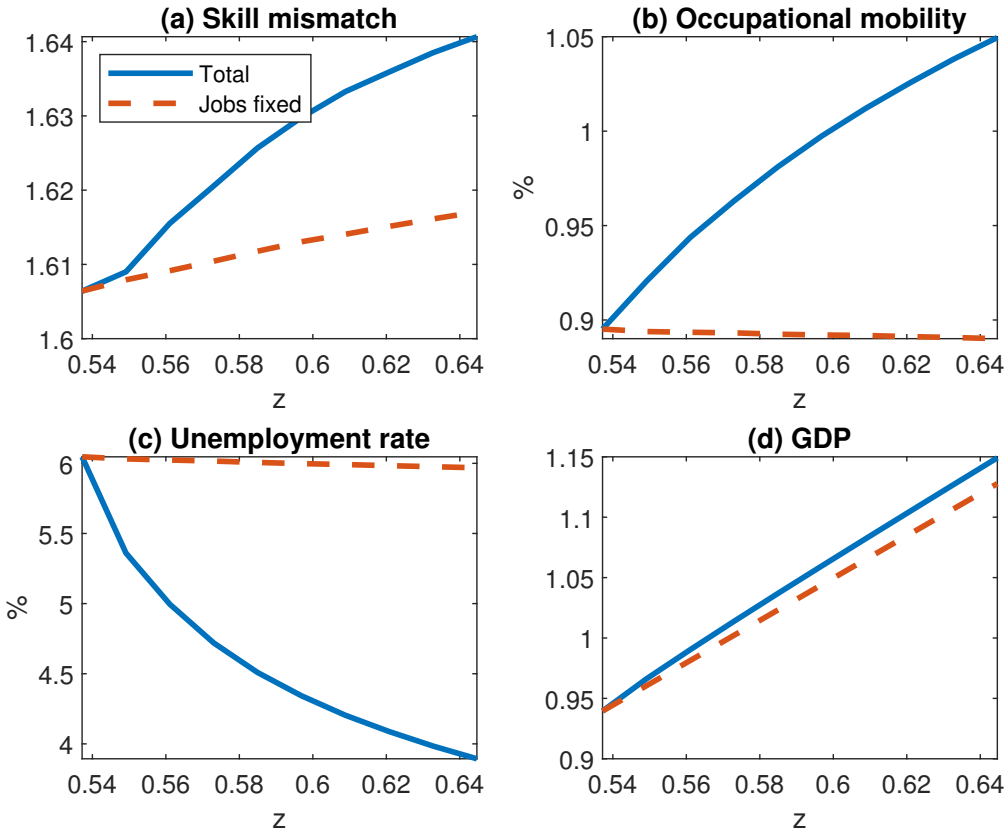
since more employment pairs have positive match surplus and promotes more occupational switches. This will create more sorting in the economy and affect skill mismatch which becomes lower. On the other hand, higher productivity entails that unemployed workers are willing to accept more jobs, even for those with relatively high mismatch since now the match surplus is higher. These will lead to a rise in aggregate skill mismatch. Therefore, given these two opposing effects, the impact on skill mismatch will depend on which effect dominates. Quantitatively, the combined effects lead to a small increase in overall mismatch level as the mismatch measure increases by merely 2%.

As mentioned above, the occupational mobility rate is higher as the aggregate productivity grows. This happens as the total match surplus increases which encourages more vacancies to enter the market increasing the job finding rate. Since there are more jobs available in the economy, it is more likely that an employed worker would be able to find a better matched occupation in the market. Thus, the occupational mobility rate becomes larger by roughly 0.1 percentage point. Finally, there is a negative effect on the unemployment rate (-1.5 percentage points) which is driven by the higher vacancy creation (and job finding rate) and a positive effect on GDP (+20%) since there is a 1-to-1 mapping between the aggregate productivity factor and GDP. We conclude that as the economy grows, we would observe on average worse matched workers and jobs, but more mobility between occupations.

How much of the above aggregate changes are due to the general equilibrium effects through firm entry and changing number of jobs? To isolate the general equilibrium effects, we consider the same increase of the aggregate productivity factor z as before but re-do the analysis only for a partial equilibrium version of the model where the number of jobs n is fixed at the baseline level[28] (we called this case "Jobs fixed" in Figure 8). We can see that the direction of the effects in the partial equilibrium case are generally the same as in the general equilibrium case. However, the quantitative impact is much lower when we do not allow changes in the job finding rate and vacancy filling rate. Note that now the occupational mobility and unemployment rate barely change. Moreover, the average skill mismatch increases by merely 0.7% under the partial equilibrium case. Therefore, most of the changes in skill mismatch and unemployment rate is due to the general equilibrium effects. The opposite is true for the aggregate output, where the overall effect is barely different from the partial equilibrium effect. We conclude that quantitatively there is amplification

[28]In Appendix E, we also consider the case when θ is fixed. In this case, contact rates are kept constant as well. The model is thus similar to that in Lise and Postel-Vinay (2020). We get similar results in the partial equilibrium.

Figure 8: **Effects of Aggregate Productivity**



by the general equilibrium effects, which are very pronounced in occupational mobility and unemployment rate.

5.6 Unemployment Benefits

The model developed in the previous section allows us to evaluate the impact of labor policies on skill mismatch and occupational mobility. Here we consider the case of changing unemployment benefits[29]. This is equivalent to changing the parameter b in the model. We consider the case when b increases from 0.4 (baseline) to 0.44, a 10% surge.

Figure 9 shows that the effects on aggregate skill mismatch, occupational mobility, unemployment rate and GDP. When unemployment benefits increase the outside option of the workers increases as well. As a result, a smaller number of matches carry positive surplus

[29]In Appendix E, we consider the policy of reducing search friction.

and so there is less jobs created in the economy. Thus, workers have to work in some worse matched jobs which leads to an increase in the aggregate skill mismatch. While the unemployment benefit increases by 10%, the aggregate mismatch rises by 5%. In addition, since there are in general less jobs available to search, both the job finding rate and the probability of meeting with a job with positive surplus decline, leading to a lower occupational mobility rate. Quantitatively, the mobility rate decreases from 0.90% to 0.76%. Finally, since the outside option value increases, this would lead to a positive effect on the unemployment rate (+9 percentage points) driven by the lower vacancy filling rates and a negative effect on aggregate output (−8%).

The general equilibrium effects are more pronounced than in the case of aggregate productivity growth. For the partial equilibrium case we continue to keep constant the number of jobs. By increasing the unemployment benefits, the four variables of interest (skill mismatch, occupational mobility, unemployment rate, and GDP) are barely impacted[30] (see Figure 9 - "Jobs fixed). For example, the aggregate output drops only 0.1% in the partial equilibrium case. Therefore, most of the impact on these aggregate variables is due to the general equilibrium effects. Taking this into consideration is of great importance when designing policies that impact the labor market and translates to effects on the aggregate economy.

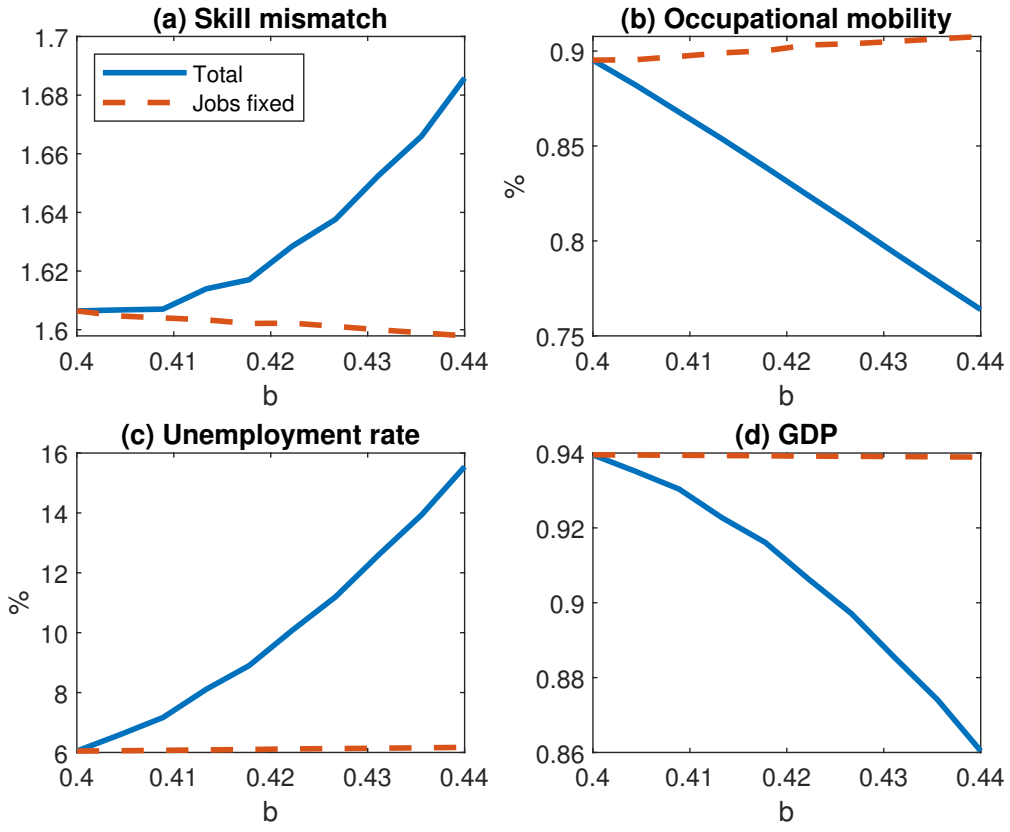
6 Conclusion

In this paper, we study the connection between skill mismatch and labor mobility and its aggregate consequences. We show empirically that in general higher skill mismatch induces workers to move to a better matched occupation. Moreover, labor mobility helps reduce skill mismatch, especially for those previously with high skill mismatch. In this regard, we find that occupational mobility is more effective than geographical mobility in reducing skill mismatch. Also, negative mismatch is shown to have negative effect on job separations.

Our quantitative model shows that skill mismatch has an important role to play in affecting the labor mobility decisions, as well as the aggregate economy. Two-thirds of the total skill mismatch is due to search frictions which costs about 1% of output and welfare. The multidimensionality of skills hinders the improvement of skill mismatch. Human capital accumulation helps with sorting of workers to their job and would reduce mismatch and

[30] Interestingly, skill mismatch actually slightly decreases as b increases. This is likely due to the selection effect: as less able and worse matched individuals are driven into unemployment, the remaining matches carry lower mismatch on average.

Figure 9: **Effects of Unemployment Benefit**



occupational mobility. We find that aggregate productivity has a positive impact on both the skill mismatch and occupational mobility. This implies that as the economy grows, we would observe on average worse matched workers and jobs, but more mobility between occupations. Lastly, we find that increasing unemployment benefit would raise the skill mismatch but lower the occupational mobility in the economy. As a result, unemployment rate rises while the total output drops.

There are a few promising extensions of our model. First, our model abstracts from life-cycle features which could be important to explain the life-cycle dynamics of wage growth and mobility. Extending our model to a life-cycle setting, and incorporating education and on-the-job learning would allow us to study skill mismatch and mobility over the life-cycle. Second, we do not consider geographical mobility in our baseline calibration. By introducing a moving cost function and different job distributions in different locations, our model would be able to explain the geographical mobility in the data.

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Appendices

A Data Appendix

A.1 Data Construction

In this appendix, we lay out the details about our data construction process. The NLSY contains information about the weekly employment status of individuals and the occupational information about their jobs conditional on being employed. For each year in our sample, we define the primary job held by the individuals as the job which they worked the most hours in. With this we obtain a yearly panel of individuals with their corresponding primary job and demographic characteristics. We drop those individuals with invalid ASVAB score or when they are enrolled in school. All wages are deflated to 2000 price level using the US Consumer Price Index.

We convert all occupational codes into the three-digit 1990 census occupational code. Geographic location information is from the restricted Geocode file which contains the FIPS code of the location of residence. We convert the FIPS location to commuting zone using the 2000 commuting zone clustering from the U.S. Department of Agriculture[31]. As mentioned before, we identify occupational mobility when the individual switches occupation and job at the same time, geographical mobility the individual moves from one commuting zone to another, and job separation she transitions from employment to unemployment.

To construct the skill measures of individuals, we follow Guvenen et al. (2020) to use individual components of the ASVAB test. Specifically, after normalizing the test scores to have a standard deviation of one, we compute the verbal skill measure as the first principal component of Word Knowledge and Paragraph Comprehension scores and math ability measure as the first principal component of Arithmetic Reasoning and Mathematics Knowledge scores. For the NLSY79, the social skill measure is taken as the first principal component of the normalized scores from the Rotter Locus of Control Scale and Rosenberg Self-Esteem Scale.

[31] We use the cross-walk file publicly available at `https://www.ers.usda.gov/data-products/commuting-zones-and-labor-market-areas/`.

Table A.1: List of Skills in O*NET

Verbal and Math Skills	
1. Oral Comprehension	2. Written Comprehension
3. Deductive Reasoning	4. Inductive Reasoning
5. Information Ordering	6. Mathematical Reasoning
7. Number Facility	8. Reading Comprehension
9. Mathematics Skill	10. Science
11. Technology Design	12. Equipment Selection
13. Installation	14. Operation and Control
15. Equipment Maintenance	16. Troubleshooting
17. Repairing	18. Computers and Electronics
19. Engineering and Technology	20. Building and Construction
21. Mechanical	22. Mathematics Knowledge
23. Physics	24. Chemistry
25. Biology	26. English Language
Social Skills	
1. Social Perceptiveness	2. Coordination
3. Persuasion	4. Negotiation
5. Instructing	6. Service Orientation

For the NLSY97, we use four personality scales[32] and a self-rated life satisfaction question[33] to define the social skill measures. These scales are chosen to match those psychological scales in the NLSY79. Finally, all skill measures are converted into percentile scores.

To construct the skill requirements components we use the O*NET database and closely follow the procedures developed in Guvenen et al. (2020) who construct the math, verbal and social skills by getting the weighted average of selected O*NET descriptors (Table A.1 presents a replica of Table C.3 in their paper with the list of skills taken into consideration) and performing a Principal Component Analysis (PCA). From the available O*NET collection of files we only use the ones related to abilities, knowledge and skills. We only consider the "importance" score and not the "level", which is the standard in the literature. Additionally, O*NET's occupations are coded using the *Standard Occupational Classification (SOC)*, however, they are converted into the Three-Digit Census Occupation Classification

[32]The relevant question is as follows: "Using a scale from 1 to 7, where 1 means disagree strongly and 7 means agree strongly, please rate how well each pair of traits applies to you, even if one characteristic applies more strongly than the other." Our choices of traits are "Extraverted, Enthusiastic", "Dependable, Self-disciplined", "Open to new experiences, Complex", and "Disorganized, Careless".

[33]The relevant question is "All things considered, how satisfied are you with your life as a whole these days?".

to match the occupational codes in the NLSY. For doing so, we take the average score of the occupation codes of the SOC that maps into a unique corresponding occupation from the Census classification [34]. We weight each occupation using the number of observations for each occupation in the individual dataset for the NLSY79 cohort.

The math, verbal and social components are derived from the O*NET's descriptors in Table A.1 which are aggregated following the same methodology as in Guvenen et al. (2020). In particular, the O*NET skills are converted into 4 ASVAB test categories: arithmetic reasoning, mathematics knowledge, word knowledge and paragraph comprehension [35]. Then, the 26 O*NET descriptors are selected and assigned a relatedness score to each of the 4 categories where an O*NET analog was created by summing the 26 descriptors and weighting them by the relatedness score. Each dimension's standard deviation is normalized to one, and the 4 categories are reduced into 2 dimensions, verbal and math, by applying a Principal Component Analysis (PCA). The verbal score is the first principle component of Word Knowledge and Paragraph Comprehension, and the math score is that of Math Knowledge and Arithmetic Reasoning. For the social component, the six O*NET descriptors from Table A.1 are reduced to a single dimension by taking the first principal component after normalizing each dimension's standard deviation to one. Finally, these scores are converted into percentile rank scores among occupations.

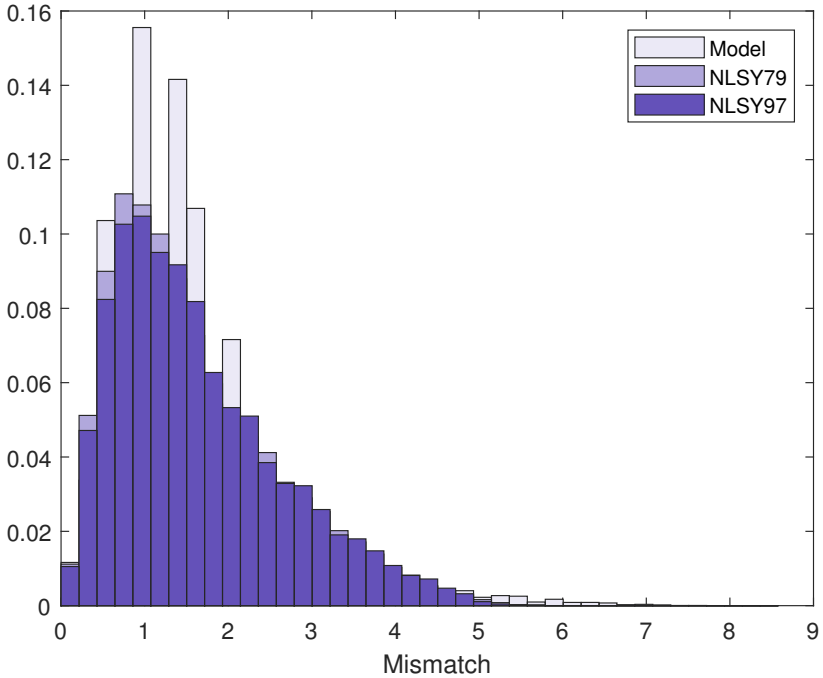
The skill mismatch measures are then computed using the definitions (1) to (4). The weights used in (2) to (4) are obtained by first running a PCA on the set of component-wise mismatch measures, and then normalizing the factor loadings on the first principal component to sum to one. All mismatch measures are normalized to have a standard deviation of one.

[34] Crosswalks between the Standard Occupational Classification and the Three-Digit Census Occupation Classification are available at `https://www.census.gov/topics/employment/industry-occupation/guidance/code-lists.html`

[35] Crosswalk available at "*The ASVAB Career Exploration Program: Theoretical and Technical Underpinnings of the Revised Skill Composites and OCCU-Find*"

A.2 Skill Mismatch Distribution

Figure A.1: **Skill Mismatch Distribution by Cohort**



Notes: Mismatch is defined as the misalignment of worker's skill set with respect to the skill requirement of a job.

A.3 Summary Statistics

Table A.2 shows the summary statistics (using an annual frequency) and demographic composition of the main data set[36]. In general, the mobility indicators tend to be higher for those individuals in NLSY97. Behind this pattern hides a pure age effect given that every individual in the NLSY97 sample is less than 35 years old with an average age of 25 years old. Taking this effect into consideration, we look into the mobility rates by age groups. For both cohorts, there is a negative relationship between age and mobility; this is, when we increase age the mobility rates decrease. In particular, those individuals with less than 25 years old tend to change occupations more frequently, with an occupational mobility rate of 50% and 33%, and a geographical mobility rate of 11% and 5%,respectively for NLSY79 and NLSY97. While for those individuals between 25-34 years old occupational mobility is 22% and 11% and geographical mobility, 4% and 2%, for the respective cohorts. There has also been a

[36]Table A.3 presents the summary statistics using a monthly frequency for occupational mobility and job separation since the targeted moments in Section 5.2 are done using this same frequency.

change in the composition of the sample by education where for the younger cohort higher education levels are attained and conditional on the completed education group a negative correlation exists with respect to occupational/geographical mobility. For example, a high school drop out from NLSY79 will switch occupations at a rate of 26% yet a 4-year college individual will switch almost at half of this rate. This negative correlation between occupational mobility and age or educational level, confirms the evidence presented in Kambourov, Manovskii and Plesca (2018), Guvenen et al. (2020) and Moscarini and Thomsson (2007). By gender, there is not a significant difference between groups regarding mobility; nonetheless, by marital status single individuals switch occupations and relocate more frequently, since the opportunity cost of moving is lower relative to those who are married.

In regard to job separation, overall those in the NLSY97 sample tend to separate from their job with a higher rate than those in the NLSY79 sample. However, we must take into account the age selection of each of these samples. Individuals in the NLSY79 used to separate more often from their jobs (14%) when they were less than 25 years of age than those in the NLSY97 for the same age group (9%). This difference can also be related to the fact that educational attainment has increased over time, hence those individuals in the younger cohort tend to stay longer in school, and decide to enter the labor market later in life causing the effect to be delayed. In this sense, we see how individuals between ages 25-34 in NLSY97 separate from their jobs at a rate of 11%, a higher rate than the youngest age group within the same cohort. A negative correlation is also seen between job separation and educational level, yet it is not clear with respect to age group for either cohort. By gender we find that women in both cohorts, tend to separate from their jobs more often. This supports the literature related to women labor supply and can be related to the discussion regarding fertility, as well.

With respect to average skill mismatch, women and single individuals tend to have higher levels of mismatch. Second, with respect to age, there exists a negative correlation between mismatch and age. Third, the relationship between mismatch and educational level is not clear where individuals with some college education are the ones with the highest level of mismatch.

Table A.2: **Summary Statistics**

	NLSY79					NLSY97				
	%	Mismatch	Occ. Mob.	Geo. Mob.	Job Sep.	%	Mismatch	Occ. Mob.	Geo. Mob.	Job Sep.
Overall										
All	100.00	1.62	15.57	2.24	7.75	100.00	1.69	20.68	3.13	10.28
Gender										
Men	50.66	1.58	15.84	2.42	5.94	52.36	1.68	20.60	3.18	6.81
Women	49.34	1.67	15.25	2.02	9.95	47.64	1.69	20.77	3.08	14.10
Race										
White	79.21	1.63	15.21	2.30	7.30	73.84	1.73	20.55	3.40	9.12
African-American	14.38	1.54	17.66	1.97	10.06	15.76	1.49	21.73	2.36	16.13
Others	6.41	1.62	16.06	1.92	8.86	10.40	1.64	20.14	2.42	9.53
Marital Status										
Married	54.51	1.59	11.46	1.40	6.64	33.11	1.61	13.65	2.17	11.25
Single	45.49	1.66	21.99	3.61	9.12	66.89	1.73	23.96	3.53	9.83
Age Group										
$<$ 25 y/o	21.52	1.80	49.91	11.27	14.48	45.85	1.80	33.28	4.72	8.60
25-34 y/o	36.41	1.66	22.00	3.61	8.05	53.65	1.63	11.28	1.58	11.30
35-44 y/o	21.87	1.58	10.72	1.33	3.91	.	.	.	.	.
$\geq$ 45 y/o	20.20	1.56	6.78	0.53	5.19	.	.	.	.	.
Completed Education										
$<$ High School	12.55	1.60	26.08	3.78	14.19	18.57	1.57	27.21	3.12	20.59
Compl. High School	46.78	1.71	16.93	2.22	8.82	30.03	1.73	23.33	2.91	10.97
Some College	19.96	1.71	14.69	2.07	6.49	21.29	1.86	19.51	3.21	8.45
4-year College	12.98	1.52	12.33	2.16	4.42	15.56	1.67	16.63	3.69	3.87
$>$ 4-year College	7.73	1.23	8.00	1.62	3.40	14.54	1.52	12.33	2.94	4.37

Notes: See Section 3.2 for the construction of the skill mismatch measure. Occupational mobility is defined as the change of occupation from one year to another accompanied by a job switch. Geographical mobility is conditional on an occupational switch occurring and the re-location of the individual to another commuting zone. Job separation is defined as the transition from being employed to non-employed from one interview year to another.

Table A.3: **Summary Statistics (Monthly)**

	NLSY79		NLSY97	
	Occ. Mob.	**Job Sep.**	**Occ. Mob.**	**Job Sep.**
Overall				
All	0.91	20.74	3.85	18.40
Gender				
Men	0.92	13.53	3.86	14.17
Women	0.89	28.14	3.84	23.05
Race				
White	0.91	18.70	3.84	16.42
African-American	0.94	29.66	4.07	27.65
Others	0.87	25.89	3.61	18.54
Marital Status				
Married	0.71	19.02	2.37	16.50
Single	1.23	22.80	4.58	19.33
Age Group				
$<$ 25 y/o	2.42	26.54	6.60	20.79
25-34 y/o	1.15	20.06	2.76	16.65
35-44 y/o	0.83	16.10	.	.
$\geq$ 45 y/o	0.50	20.80	.	.
Completed Education				
$<$ High School	1.29	40.12	5.45	34.90
Compl. High School	0.95	21.74	4.34	19.94
Some College	0.90	16.39	3.45	15.59
4-year College	0.81	11.56	2.87	8.14
$>$ 4-year College	0.63	9.87	2.50	8.91

Notes: Occupational mobility in this case is defined as the change of occupation from one month to another that is accompanied by a job switch. Job separation is defined as the transition from being employed to non-employed from one month to another.

B Additional Regressions Tables

Table B.1: **Regression Results: Monthly Occupational Mobility**

VARIABLES	(1) Logit	(2) Logit	(3) Logit	(4) Logit	(5) Logit	(6) Logit
			NLSY79			
Mismatch	0.0876***	0.0670***				
	(0.00842)	(0.0111)				
Positive Mismatch			0.134***	0.150***		
			(0.00939)	(0.0134)		
Negative Mismatch			0.0172	-0.0408***		
			(0.0107)	(0.0143)		
Verbal Mismatch					0.0542***	0.0393**
					(0.0114)	(0.0155)
Math Mismatch					0.0393***	0.0288*
					(0.0115)	(0.0152)
Social Mismatch					0.0147*	0.0277**
					(0.00884)	(0.0125)
Constant	-1.887***		-1.933***		-1.888***	
	(0.157)		(0.157)		(0.157)	
Observations	1,622,709	1,027,309	1,622,709	1,027,309	1,622,709	1,027,309
Number of pid		5,398		5,398		5,398
			NLSY97			
Mismatch	0.100***	0.101***				
	(0.00588)	(0.00826)				
Positive Mismatch			0.136***	0.177***		
			(0.00669)	(0.0101)		
Negative Mismatch			-0.0180**	-0.0369***		
			(0.00759)	(0.0100)		
Verbal Mismatch					0.0647***	0.0683***
					(0.00776)	(0.0112)
Math Mismatch					0.0454***	0.0432***
					(0.00774)	(0.0108)
Social Mismatch					0.0133**	0.00880
					(0.00617)	(0.00866)
Constant	1.949***		1.790***		1.947***	
	(0.192)		(0.193)		(0.193)	
Observations	668,275	614,970	668,275	614,970	668,275	614,970
Number of pid		5,221		5,221		5,221
Controls	YES	YES	YES	YES	YES	YES
Individual FE	NO	YES	NO	YES	NO	YES

Notes: Controls includes age, age-squared, gender, race, completed education level, marital status, and unemployment rate at the national level. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table B.2: **Regression Results: Monthly Job Separation**

VARIABLES	(1) Logit	(2) Logit-FE	(3) Logit	(4) Logit-FE	(5) Logit	(6) Logit-FE
			NLSY79			
Mismatch	0.0276***	0.00735				
	(0.00614)	(0.00836)				
Verbal Mismatch			0.0316***	0.0152		
			(0.00805)	(0.0112)		
Math Mismatch			-0.00462	-0.00727		
			(0.00812)	(0.0111)		
Social Mismatch			0.0122*	0.00127		
			(0.00626)	(0.00918)		
Positive Mismatch					0.0563***	0.0517***
					(0.00704)	(0.0105)
Negative Mismatch					-0.0128*	-0.0377***
					(0.00750)	(0.0102)
Constant	-0.562***		-0.571***		-0.590***	
	(0.0946)		(0.0948)		(0.0947)	
Observations	1,671,876	1,359,426	1,671,876	1,359,426	1,671,876	1,359,426
Number of pid		8,133		8,133		8,133
			NLSY97			
Mismatch	-0.00709**	0.0598***				
	(0.00339)	(0.00560)				
Verbal Mismatch			0.0184***	0.0772***		
			(0.00428)	(0.00726)		
Math Mismatch			-0.0269***	-0.00840		
			(0.00425)	(0.00695)		
Social Mismatch			0.00264	-0.000691		
			(0.00325)	(0.00555)		
Positive Mismatch					0.0189***	0.197***
					(0.00400)	(0.00725)
Negative Mismatch					-0.0640***	-0.0937***
					(0.00367)	(0.00597)
Constant	-0.00198		-0.0195		-0.120	
	(0.108)		(0.108)		(0.108)	
Observations	669,054	569,638	669,054	569,638	669,054	569,638
Number of pid		4,791		4,791		4,791
Controls	YES	YES	YES	YES	YES	YES
Individual FE	NO	YES	NO	YES	NO	YES

Notes: Controls includes age, age-squared, gender, race, completed education level, marital status, and unemployment rate at the national level. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table B.3: **Regression Results: Occupational Mobility Full-Time Workers**

VARIABLES	(1) Logit	(2) Logit-FE	(3) Logit	(4) Logit-FE	(5) Logit	(6) Logit-FE
			NLSY79			
Mismatch	0.0525***	0.0303**				
	(0.0103)	(0.0147)				
Positive Mismatch			0.0633***	0.0740***		
			(0.0123)	(0.0193)		
Negative Mismatch			0.0428***	-0.00287		
			(0.0117)	(0.0168)		
Verbal Mismatch					0.0329**	0.0173
					(0.0136)	(0.0198)
Math Mismatch					0.0203	0.0137
					(0.0137)	(0.0196)
Social Mismatch					0.0182*	0.0113
					(0.0102)	(0.0161)
Constant	2.772***		2.764***		2.762***	
	(0.210)		(0.210)		(0.210)	
Observations	98,659	64,128	98,659	64,128	98,659	64,128
Number of pid		4,914		4,914		4,914
			NLSY97			
Mismatch	0.0821***	0.0913***				
	(0.0161)	(0.0256)				
Positive Mismatch			0.114***	0.139***		
			(0.0189)	(0.0322)		
Negative Mismatch			0.0214	0.0282		
			(0.0178)	(0.0277)		
Verbal Mismathc					0.0414**	0.0623*
					(0.0209)	(0.0338)
Math Mismatch					0.0405*	0.0377
					(0.0207)	(0.0324)
Social Mismatch					0.0620***	0.0218
					(0.0155)	(0.0260)
Constant	-7.593***		-7.660***		-7.669***	
	(0.681)		(0.681)		(0.682)	
Observations	32,966	21,165	32,966	21,165	32,966	21,165
Number of pid		2,814		2,814		2,814
Controls	YES	YES	YES	YES	YES	YES
Individual FE	NO	YES	NO	YES	NO	YES

Notes: A worker is considered to work full-time if it reports to have worked in a week more than 35 hours. Controls include age, age-squared, gender, race, completed education level, marital status, and unemployment rate at the national level. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table B.4: **Regression Results: Log-Wages (NLSY79)**

VARIABLES	(1) OLS	(2) OLS	(3) OLS
Math Mismatch	-0.0185***	-0.0165***	-0.0161***
	(0.00199)	(0.00189)	(0.00186)
Verbal Mismatch	-0.0319***	-0.0273***	-0.0261***
	(0.00199)	(0.00189)	(0.00185)
Social Mismatch	-0.0113***	-0.0133***	-0.0134***
	(0.00155)	(0.00147)	(0.00144)
Math Ability	0.435***	0.413***	0.309***
	(0.00910)	(0.00866)	(0.00872)
Verbal Ability	0.0724***	0.0876***	0.146***
	(0.00904)	(0.00859)	(0.00894)
Social Ability	0.175***	0.186***	0.170***
	(0.00581)	(0.00549)	(0.00545)
Math Requirements	-0.189***	-0.0882***	-0.131***
	(0.0148)	(0.0139)	(0.0136)
Verbal Requirements	1.071***	0.874***	0.806***
	(0.0161)	(0.0152)	(0.0148)
Social Requirements	-0.211***	-0.222***	-0.133***
	(0.00698)	(0.00660)	(0.00686)
Constant	1.935***	1.659***	1.670***
	(0.00469)	(0.00558)	(0.0281)
Observations	114,589	114,589	114,589
R-squared	0.284	0.359	0.386
Demographic Controls	NO	YES	YES
Employment Controls	NO	NO	YES

Notes: Demographic controls include age, age-squared, gender, race, completed education level and marital status. Employment controls include employment tenure, employment tenure squared, occupational tenure, occupational tenure squared and cubed, experience, experience squared and cubed, and unemployment rate at the national level. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

C Computational Appendix

We follow Lise et al. (2016) to compute the equilibrium of the model. Specifically, given the exogenous distributions of abilities $l(\mathbf{a})$ and skill requirements $\gamma(\mathbf{r})$, and an initial guess of market tightness, distribution of matches, and match surplus $\{\theta, m(\mathbf{a},\mathbf{r}), S(\mathbf{a},\mathbf{r})\}$, we employ the following iteration algorithm:

1. Compute the meeting rates using (18) to (21).

2. Calculate the density of unemployment and aggregate unemployment rate by

$$\begin{aligned} u(\mathbf{a}) &= l(\mathbf{a}) - \int_{\mathbf{r}} m(\mathbf{a},\mathbf{r}) d\mathbf{r} \\ u &= \int_{\mathbf{a}} u(\mathbf{a}) d\mathbf{a} \end{aligned}$$

3. Compute the measure of vacancies and jobs,

$$\begin{aligned} v &= [u + \xi(1-u)]\,\theta \\ n &= v + 1 - u \\ n(\mathbf{r}) &= n\gamma(\mathbf{r}) \\ v(\mathbf{r}) &= n(\mathbf{r}) - \int_{\mathbf{a}} m(\mathbf{a},\mathbf{r}) d\mathbf{a} \end{aligned}$$

4. Compute the value of vacancy $V^V(\mathbf{r})$:

$$\begin{aligned} (1-\beta)V^V(\mathbf{r}) &= -c + \beta q^u \int_{\mathbf{a}} (1-\eta_0) \max\{S(\mathbf{a},\mathbf{r}), 0\}\, dF^u(\mathbf{a}) \\ &\quad + \beta q^e \int_{\mathbf{r}'} \int_{\mathbf{a}} (1-\eta_0) \max\{S(\mathbf{a},\mathbf{r}) - S(\mathbf{a},\mathbf{r}'), 0\}\, dF^m(\mathbf{a},\mathbf{r}') \end{aligned}$$

Let

$$\{\mathbf{r}^*\} = \arg\min_{\mathbf{r}} V^V(\mathbf{r})$$

5. Update the measure of matches $m(\mathbf{a},\mathbf{r})$ using (31),

$$m'(\mathbf{a},\mathbf{r}) = \frac{\left[\rho^u u(\mathbf{a}) + \rho^e \int\limits_{S(\mathbf{a},\mathbf{r}')<S(\mathbf{a},\mathbf{r})} m(\mathbf{a},\mathbf{r}')d\mathbf{r}'\right] f^v(\mathbf{r})}{s+(1-s)\rho^e \int\limits_{S(\mathbf{a},\mathbf{r})<S(\mathbf{a},\mathbf{r}')} f^v(\mathbf{r}')d\mathbf{r}'} \mathbf{1}\left\{S(\mathbf{a},\mathbf{r}) \geq 0\right\}$$

6. Update the surplus function using (22):

$$\begin{aligned} S'(\mathbf{a},\mathbf{r}) &= \phi(\mathbf{a},\mathbf{r}) - b(\mathbf{a}) + \beta(1-s)\left[\rho^e \int_{\mathbf{r}'} \tilde{S}(\mathbf{a},\mathbf{r};\mathbf{r}')dF^v(\mathbf{r}') + (1-\rho^e)S(\mathbf{a},\mathbf{r})\right] \\ &\quad -\beta\rho^u \int_{\mathbf{r}'} \max\left\{\eta_0 S(\mathbf{a},\mathbf{r}'),0\right\} dF^v(\mathbf{r}') - (1-\beta)V^V(\mathbf{r}) \end{aligned}$$

7. Update the market tightness θ using the free entry condition (16),

$$\theta' = \left\{ \frac{c}{\beta A(1-\eta_0)\left[\begin{array}{c} \int_{\mathbf{a}} \max\left\{S(\mathbf{a},\mathbf{r}^*),0\right\} dF^u(\mathbf{a}) \\ +\xi \int_{\mathbf{r}'} \int_{\mathbf{a}} \max\left\{S(\mathbf{a},\mathbf{r}^*) - S(\mathbf{a},\mathbf{r}'),0\right\} dF^m(\mathbf{a},\mathbf{r}') \end{array}\right]} \right\}^{\frac{-1}{\alpha}}$$

8. Repeat until convergence of $\left\{\theta, m(\mathbf{a},\mathbf{r}), S(\mathbf{a},\mathbf{r})\right\}$.

9. In the case when the number of jobs is fixed, calculate the measure of vacancies and market tightness as follows (no need for the convergence of θ in this case):

$$\begin{aligned} v &= n+u-1 \\ \theta &= \frac{v}{[u+\xi(1-u)]} \end{aligned}$$

D Alternative Skill Mismatch Measures

In this Section we describe two alternative methods to construct a one-dimensional skill mismatch measure. We argue that the multidimensional measure proposed by Guvenen et al. (2020) and used in this paper has more predictive value relative to the alternative measures and goes in line with the economic intuition regarding the relationship between skill mismatch and labor mobility discussed in this paper and seen in the data.

D.1 Mismatch Measure from Latent Wage

We construct a measure of "ideal wages" under which deviations of such measures are interpreted as mismatch between workers and firms. However, as usual the data only allows us to observe the distribution of accepted wages and not the distribution of offered wages. Therefore, we use a two-step estimation method developed by Heckman (1979) for sample selection models to correct the specification error for the case of censored samples.

The standard selection model specification is as follows. Let y_2^* be our outcome of interest (wages) and y_1^* be the latent variable (whether or not to work). Therefore, y_2^* is only observed if $y_1^* > 0$. In particular, for each individual i, the linear model is given by

$$\begin{aligned} y_1^* &= \boldsymbol{X}_1'\beta_1 + \epsilon_1 \\ y_2^* &= \boldsymbol{X}_2'\beta_2 + \epsilon_2 \end{aligned} \tag{D.1}$$

where $\boldsymbol{X}_1$ and $\boldsymbol{X}_2$ are control variables such as age, age-squared, gender, race, educational level, marital status, employment and occupational tenure, experience, workers' abilities (math, verbal and social) and job requirements (math, verbal and social). Since the errors are correlated, then the parameter estimates, β_2, will be inconsistent if we solely use an OLS regression. Due to this caveat, we implement Heckman's two-step procedure which augments the OLS regression by an estimate of the omitted variables which corresponds to the inverse Mills ratio. Recall that y_{1i}^* corresponds to labor force participation status for individual i; then, for the first step we run a probit regression of y_1 on $\boldsymbol{X}_1$. Taking the predicted values we are able to estimate the inverse Mills ratio $\lambda(\boldsymbol{X}_1'\hat{\beta}_1) = \frac{\phi(\boldsymbol{X}_1'\hat{\beta}_1)}{\Phi(\boldsymbol{X}_1'\hat{\beta}_1)}$, where $\Phi(\cdot)$ and $\phi(\cdot)$ correspond to a standard normal cdf and pdf, respectively[37]. Further, we proceed with the

[37]Ideally, for the selection equation we would have prefer to estimate the probability of participation in each occupation rather than the probability of participation in the labor market or not. However, a limitation

second step by running the augmented OLS regression; this is, for individual i,

$$y_2 = \boldsymbol{X}_2'\beta_2 + \sigma_{12} \times \lambda(\boldsymbol{X}_1'\hat{\beta}_1) + \nu \tag{D.2}$$

where ν is the OLS residual and $\sigma_{12} = corr(\epsilon_1, \epsilon_2)$ is the correlation term of the errors.

To calculate a proxy of "ideal wages" we use the estimated coefficients from the two-step procedure and calculate wages by replacing workers' abilities values (math, verbal and social) with the job requirements values (math, verbal and social), i.e. we are assuming a perfect alignment between abilities and requirements. Finally, the "*latent wage*" skill mismatch measure is given by the absolute difference between the predicted wages and the ideal wages. We also normalize this measure such that the standard deviation is equal to 1.

D.2 Mismatch Measure by Fixed Effects Decomposition

A different approach is one where we construct a one dimension skill measure using individual and firm fixed effects inspirited by Abowd, Kramarz and Margolis (1999). To construct this one dimension empirical measure, which we call *"AKM"* skill mismatch, we closely follow the method presented in Appendix H by Lindenlaub and Postel-Vinay (2020*a*). Let "t" the index for periods of time where $t \in \{1, \ldots, T\}$, "i" be the index for workers in the sample such that $i \in \{1, \ldots, N\}$, "j" the index for jobs such that $j \in \{1, \ldots, J\}$, $c_{it} \in \{1, \ldots, J\}$ is the occupation of worker i's employer at time t and $S(a, r)$ is the flow surplus function.

Since we do not have an observable component in the data to match $S(a, r)$, we use wages as a proxy, $w(a, r)$ as we did before.

Worker types: Any worker's i's type, a_i, is estimated by ranking the maximum wage, $w_i(a, r)$, obtainable for each individual for all j and t in the workers sample. This is,

$$\hat{a}_i = R_W\Big(\max\{w_{i,c_{it},t} : t = 1, \ldots, T\}\Big) \tag{D.3}$$

where R_W stands for the percentile ranks for all workers. The resulting $\hat{a}_i$ will be in the

of the dataset we use is that there are not enough individuals in each occupation to be able to apply the two-step Heckman procedure and get an offer wage distribution for each one of these occupations.

interval of $[0, 1]$.

Flow surplus: Theoretically, the flow surplus generated by a match between worker i and firm (occupation) J at time t equals $S_t(a_i, r_{O_{it}})$. Empirically, we are using wages as a proxy and estimate such value as follows,

$$\widehat{S(a, r_j)} \equiv \widehat{w(a, r_j)} = mean\{w_{i,c_{it},t} : \hat{a}_i = a, O_{it} = j \text{ and } t = 1, \ldots, T\} \tag{D.4}$$

Firm types: We estimate the firm j's type, r_j as follows,

$$\hat{r}_j = R_F\Bigg(\max\{\widehat{w(a, r_j)} : a \in [0, 1]\}\Bigg) \tag{D.5}$$

where R_F stands for the percentile ranks for the population of firms (occupations). The resulting $\hat{r_j}$ will be in the interval of $[0, 1]$.

One Dimension Empirical Measure: Since we have the estimates for $(\hat{a}_i, \hat{r_j})$ types, then we are able to get the absolute difference between the worker's and firm's types; i.e.

$$m_i^{1d} = |\hat{a}_i - \hat{r_j}| \tag{D.6}$$

Table D.1 provides the comparison of the three skill mismatch measures discussed in the paper for the empirical analysis regarding the relationship between skill mismatch and labor mobility (occupational mobility, geographical mobility and job separation). As mentioned above, the main empirical measure which allows for multidimensional skills has more predictive value relative to the latent wage and AKM skill mismatch measures. In addition, our main measure also goes in line with the economic intuition of the paper and the stylized facts from the data regarding the relationship between skill mismatch and labor mobility.

Table D.1: **Regression Results: Comparison Between Three Skill Mismatch Measures**

	NLSY79						NLSY97					
	(1) Logit	(2) Logit-FE	(3) Logit	(4) Logit-FE	(5) Logit	(6) Logit-FE	(7) Logit	(8) Logit-FE	(9) Logit	(10) Logit-FE	(11) Logit	(12) Logit-FE
Occupational Mobility												
Multidimensional Mismatch	0.0598***	0.0486***					0.0932***	0.0892***				
	(0.00920)	(0.0130)					(0.0110)	(0.0168)				
AKM Mismatch (1-dim)			0.00306	-0.0251**					-0.0587***	-0.0311*		
			(0.00944)	(0.0126)					(0.0113)	(0.0159)		
Latent Wage Mismatch					-0.0295***	0.0219					0.0290**	0.0818***
					(0.0101)	(0.0140)					(0.0125)	(0.0184)
Constant	2.326***		2.414***		2.389***		-6.582***		-6.280***		-6.326***	
	(0.136)		(0.136)		(0.136)		(0.459)		(0.458)		(0.458)	
Observations	94,156	72,617	94,156	72,617	94,156	72,617	51,610	42,585	51,610	42,585	51,610	42,585
Number of pid		5,363		5,363		5,363		4,464		4,464		4,464
Geographical Mobility												
Mismatch	0.0659**	0.0153					0.168***	0.166***				
	(0.0279)	(0.0393)					(0.0258)	(0.0382)				
1Dim-Mismatch			0.00290	0.00773					-0.0416	0.0131		
			(0.0279)	(0.0386)					(0.0289)	(0.0388)		
Latent Wage Mismatch					-0.00973	-0.0157					0.113***	0.159***
					(0.0362)	(0.0473)					(0.0289)	(0.0437)
Constant	0.0798		0.189		0.186		-13.87***		-13.41***		-13.40***	
	(0.379)		(0.378)		(0.377)		(1.323)		(1.325)		(1.324)	
Observations	47,062	7,822	47,062	7,822	47,062	7,822	46,460	8,938	46,460	8,938	46,460	8,938
Number of pid		958		958		958		1,026		1,026		1,026
Job Separation												
Multidimensional Mismatch	0.00698	0.00437					-0.0343**	0.00784				
	(0.0122)	(0.0174)					(0.0163)	(0.0294)				
AKM Mismatch (1-dim)			0.0799***	-0.0146					0.164***	0.00193		
			(0.0117)	(0.0157)					(0.0148)	(0.0247)		
Latent Wage Mismatch					-0.114***	-0.0331*					-0.123***	-0.0219
					(0.0143)	(0.0199)					(0.0173)	(0.0307)
Constant	1.428***		1.303***		1.325***		-2.957***		-3.209***		-3.104***	
	(0.133)		(0.134)		(0.133)		(0.520)		(0.520)		(0.520)	
Observations	114,589	62,541	114,589	62,541	114,589	62,541	51,648	18,633	51,648	18,633	51,648	18,633
Number of pid		4,475		4,475		4,475		1,848		1,848		1,848
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Individual FE	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES

Notes: Controls include age, age-squared, gender, race, completed education level, marital status, and unemployment rate at the national level. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table D.2: **Regression Results: Log-Wages using One-Dimension Skill Mismatch (NLSY79)**

VARIABLES	(1) OLS	(2) OLS	(3) OLS
1Dim-Mismatch	-0.0554***	-0.0493***	-0.0462***
	(0.00147)	(0.00138)	(0.00136)
Worker Ability	1.264***	1.196***	1.113***
	(0.00561)	(0.00540)	(0.00584)
Occ. Requirements	0.201***	0.168***	0.150***
	(0.00532)	(0.00498)	(0.00497)
Constant	1.867***	1.630***	1.448***
	(0.00317)	(0.00460)	(0.0268)
Observations	114,589	114,589	114,589
R-squared	0.416	0.484	0.501
Demographic Controls	NO	YES	YES
Employment Controls	NO	NO	YES

Notes: Demographic controls include age, age-squared, gender, race, completed education level and marital status. Employment controls include employment tenure, employment tenure squared, occupational tenure, occupational tenure squared and cubed, experience, experience squared and cubed, and unemployment rate at the national level. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

E Additional Quantitative Results

E.1 Calibration of the One Dimensional Model

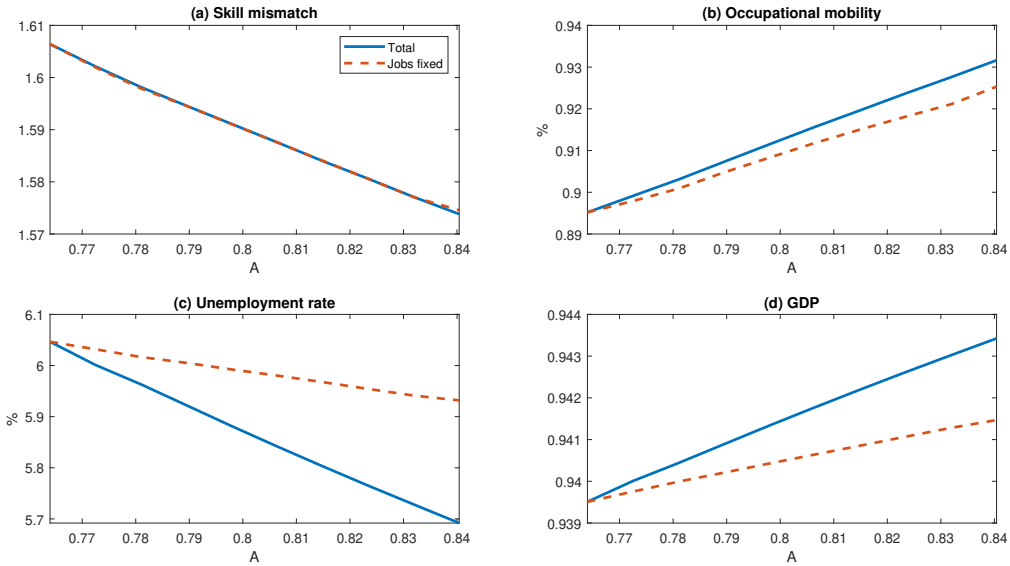
Table E.1: **Calibration of the One Dimensional Model**

Parameter	Meaning	Value	Target/source
		Preset parameters	
b	Flow utility of unemployment	0.4	Shimer (2005)
α	Matching elasticity	0.5	Petrongolo and Pissarides (2001)
η_0	Worker's bargaining power	0.5	Hosios condition
c	Cost of maintaining vacancy	0.17	Fujita and Ramey (2012)
β	Discount factor	0.9967	4% annual discount rate
		Calibrated parameters	
A	Matching efficiency	0.211	Monthly job finding rate (14.95%)
ξ	Relative search intensity of the employed	0.239	Monthly occupational mobility rate (0.91%)
s	Exogenous separation rate	0.00972	Unemployment rate (6.05%)
z	Aggregate productivity	0.5430	Average labor productivity (1.00)

E.2 Search Frictions

How would a policy of reducing search friction affect skill mismatch and occupational mobility? In the model, the matching efficiency determined by the parameter A. An increase in A therefore would reduce the search friction in the economy. Figure E.1 shows the aggregate effects of reducing search frictions. We can see that skill mismatch decreases as matching becomes more efficient. In fact, a 10% increase in matching efficiency leads to a 2% improvement in skill mismatch. Moreover, occupational mobility also increases by about 0.04 percentage point. This is natural since now it becomes easier for workers to find another jobs. As is standard in the search model, improving matching efficiency reduces unemployment as well, which entails a higher GDP in the economy. When we keep the number of jobs fixed, we can see that the effect on skill mismatch is virtually the same. We also have similar effect on occupational mobility. The general equilibrium effects are, however, much strong on unemployment and the aggregate product.

Figure E.1: **Effects of Reducing Search Frictions**



E.3 Partial Equilibrium - Fixed θ

Figures E.2 and E.3 show the effects of aggregate productivity and unemployment benefit when the market tightness θ is fixed respectively. The quantitative effects closely resemble those when the number of jobs is fixed instead. (See Figures 8 and 9)

Figure E.2: **Effects of Aggregate Productivity (Fixed θ)**

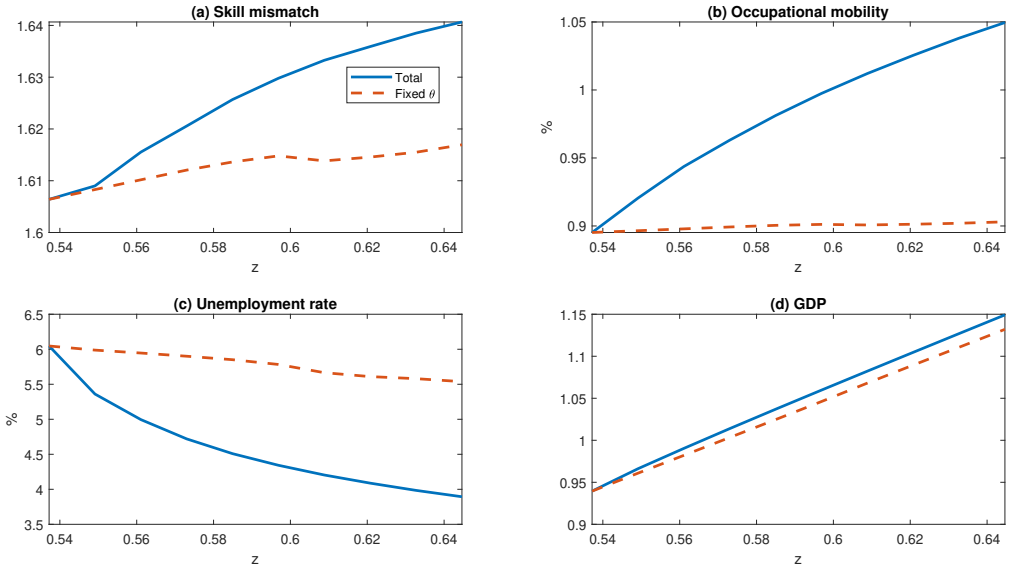


Figure E.3: **Effects of Unemployment Benefit (Fixed θ)**