Short n' Steep: Wage Growth Maximizing Job Ladders with Heterogeneous Skills and Risk Preferences

PRELIMINARY DRAFT

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Abstract

This paper examines job transitions and wage growth for young workers using detailed panel data on work histories, heterogeneous risk preferences, and a task-based measure of skill distance. It provides new evidence on how "steep" transitions—moves to jobs for which workers are relatively underskilled—affect short- and long-term wage outcomes. These transitions yield immediate wage growth premiums, contrary to the expectation that skill mismatch penalizes wage growth, suggesting productivity benefits that overshadow mismatch costs. However, it appears that workers struggle to target strictly upward moves (moves to higher-skill jobs), prompting a proposed framework in which larger transitions are riskier due to information frictions. Supporting this, risk-tolerant workers are observed to make more frequent and larger transitions, though many of these transitions are downward. A model grounded in these findings quantifies the joint implications of risk aversion and skill alignment concerns in job mobility, showing that the degree to which workers' hesitance to make larger occupational transitions is due to risk preferences versus skill deficiency has important policy implications for the efficacy of training and re-skilling programs.

1 Introduction

It is well established that job transition patterns play an important role in determining wage growth over the life cycle, often jointly and in complex interplay with human capital—a relationship that search and matching models as far back as Ben-Porath (1967) and Burdett (1978) have been trying to disentangle. At the same time, job transitions are typically characterized by substantial uncertainty, and hence risk. Therefore, variation in the riskiness of transitions, combined with heterogeneity in worker risk preferences, is a potentially meaningful driver of career trajectories and wage dispersion. This paper uses a longitudinal dataset of detailed labor market histories to document novel empirical patterns consistent with this idea, leveraging the intuitive proposition that making bigger occupational jumps (in terms of differences in skill requirements between the source and destination job) is riskier. I then propose a model of worker mobility decisions incorporating the worker's current stock of skills and heterogeneous risk appetite that can explain patterns in the data that are difficult to square with existing models of skill-based matching.

Worker human capital—or skills—impacts hiring and wages. This is clear from direct observation of job advertisements and surveys of employers, as well as a large body of work exploring the returns to increasingly specific formulations of human capital, starting with general ability or education level to industry-, occupation, or firm-specific human capital to granular skill bundles based on detailed job tasks.[1] Thus, while early matching models assumed workers were identical in terms of human capital (e.g., Burdett (1978) and Mortensen and Pissarides (1994)), this restriction was quickly relaxed (e.g., Heckman and Sedlacek (1985) and Keane and Wolpin (1997)). Canonical models incorporating human capital generally posit that workers sacrifice wage growth early in their career in order to attain more productive matches later in their career, either through investment in human capital accumulation through training or on-the-job learning or through an "exploration" or "job shopping" period that enables them to find the jobs that are the best match for their (initially uncertain) skills.[2] These models align with several stylized empirical facts, like convex wage growth, high rates of occupational switching early in one's career, and wage penalties for industry or occupation switching (Goldsmith and Veum (2002), Rubinstein and Weiss (2006), and Eckardt (2019)).

This paper examines job transitions by "skill distance" and "direction," revealing novel empirical results that both build upon and add nuance to this existing work. Using work history panel data from the National Longitudinal Survey of Youth ("NLSY") and detailed occupational skill requirements from the Occupational Information Network ("O*NET"), the skill distance of a job transition describes the absolute difference between the worker's current skill bundle at the time of transition and the skill requirements of their destination job (Guvenen et al. (2020) and Lise and Postel-Vinay (2020), and Blair, Debroy, and Heck

1. Worker human capital impacts hiring and wages as found in, e.g., Cappelli (2015), Deming and Kahn (2018), Hershbein, Macaluso, and Yeh (2018), Ziegler et al. (2020), and Brunello and Wruuck (2021). A small sample of the work exploring reruns to human capital (by level of specificity) includes: Heckman, Stixrud, and Urzua (2006), Ingram and Neumann (2006), and Lindqvist and Vestman (2011) (general ability or education level); Hashimoto (1981), Neal (1995), Lazear (2009), Kambourov and Manovskii (2009), and Sullivan (2010) (industry-, occupation-, or firm-specific human capital); Gibbons and Waldman (2004) and Autor and Handel (2013) (granular skills based on detailed job tasks).

2. See, e.g., Barron, Black, and Loewenstein (1989), Bagger et al. (2014), and Engbom (2022) for explorations of the trade-offs between short-term wage growth and human capital accumulation, and Neal (1995), Light (2005), and Antonovics and Golan (2012) for "exploration" or "job shopping" periods.

(2021) use similar skill distance measures). To capture the direction of the transition—i.e., whether the move is up or down the skill ladder—I develop additional distance measures that identify the extent to which the worker is under- or overskilled for their new job.

Considering job transitions through the lens of these skill distance and direction measures yields five key results. First, as these existing models would predict, skill mismatch appears to matter for productivity: workers moving into jobs they are initially underskilled for face wage *level* penalties relative to occupation means and are more likely to receive firm-provided training compared to well-matched or overskilled peers. Second, however, steep upward transitions yield immediate and sustained wage *growth* premiums, suggesting that job quality overshadows skill mismatch in determining wage growth. This is somewhat in contrast to the results discussed above, many of which would imply that, from a wage growth perspective, the best-case scenario is to start your career in an occupation you are already well-matched with and stay in it, or else make only small upward transitions to jobs with similar skill profiles, thus minimizing skill mismatch penalties. Third, these large upward transitions are rare, despite being extremely beneficial. While this is likely to reflect selection to some extent, the main results are robust to the inclusion of a large set of demographic and transition context controls, and remain significant after including worker fixed effects. Fourth, many workers make downward transitions, which do not appear to be driven by compensating differentials, as upward moves correlate with higher job satisfaction levels and growth after controlling for wages. This suggests that larger job transitions may be riskier due to information frictions that prevent workers from perfectly targeting higher-skill jobs.[3] Consistent with this idea, risk aversion significantly predicts the size of transitions, and larger moves carry more risk in terms of realized job outcomes.

Motivated by these empirical patterns, I introduce a model of worker transition decisions that includes heterogeneous risk preferences alongside heterogeneous skills. This model accounts for the observed wage growth premium associated with steep upward transitions and the rarity of such moves by emphasizing how information frictions and workers' risk tolerance may influence their job mobility strategies. Expanding on existing models that focus solely on skill alignment, this approach provides a more comprehensive explanation of job transition patterns, revealing the potentially important role that risk aversion plays in shaping career trajectories.

In particular, I propose a model of worker mobility decisions in which workers are heterogeneous in terms of risk aversion, skills, and education level, and larger occupational transitions are riskier due to a lack of information about skill level and quality for jobs that workers are less familiar with. In the model, workers choose an absolute skill distance range

3. It is well-documented that various information frictions exist in the labor market and significantly impact job search behavior and outcomes. For recent examples documenting the presence and implications of such frictions see, for example: Conlon et al. (2018), Wheeler (2008), Abebe et al. (2023), Banerjee and Sequeira (2023), and Mueller and Spinnewijn (2023).

in which to search for their next job, but are not able to precisely target upward moves. Intuitively, they decide whether to look for a job very similar to their current job, very different, or somewhere in between. Given a choice of search strategy, they draw a new job from a known distribution centered around their current job's skill level, with higher-skill-distance search strategies implying higher variance. The model is able to match observed transition patterns and outcomes in the data, and estimated parameters are consistent with the idea that skill match may be less important than worker characteristics and job quality in determining wages. Counterfactual exercises exploring the impact of two different active labor market policies (skills training and job search assistance) show that considering the role of risk tolerance in transition decisions has important implications for expected policy outcomes. In particular, to the extent that workers avoid larger career moves due to risk aversion rather than skill misalignment, skills training programs may be less effective than anticipated.

In sum, this paper provides the first empirical examination of the joint relationships between task-based skills, risk preferences, job transitions, and wage growth. I show that while existing models capture some elements of these dynamics, it is difficult to fully explain the nuanced interplay observed in real-world data without considering risk preferences. By incorporating risk aversion and skill mismatch into a new model of worker transition decisions, I demonstrate how these factors may jointly influence career trajectories and wage outcomes. This contribution is crucial for understanding how workers navigate complex labor markets and for designing policies that support effective job transitions and sustained wage growth.

This project contributes to a vast corpus of empirical and theoretical work on patterns of occupational mobility and wage growth over the life cycle. Exploring the wage implications of job transitions along the vectors of both *skill distance* and *skill direction*, as well as relating transition types to risk preferences, provides a new layer of insight to empirical work in this area, building on research such as Parent (2000), Light (2005), Wheeler (2008), Munasinghe, Reif, and Henriques (2008), Barlevy (2001), Kahn (2010), and Hoffmann, Laptiev, and Shi (2016) that uses U.S. survey data to carefully catalog patterns in the nature and consequences of job transitions in various contexts. From a theoretical standpoint, the model feature of workers adopting particular search or job mobility strategies in response to uncertainty, which then have downstream implications for future mobility, human capital accumulation, and wage growth, is in the spirit of work such as Neal (1999), Antonovics and Golan (2012), Pallais (2014), or more recently Deming and Noray (2020), Barbulescu and Bonet (2024), and Macaluso and Borovičková (2024). In fact, the proposed model maps quite well onto Neal's two-stage model of early-career transitions, though with significant additional complexity due to the inclusion of job skills and heterogeneous worker risk aversion. Additionally, workers in this model choose a job search strategy based on the degree of dissimilarity with their current occupation—a novel but intuitive targeting mechanism.

As touched upon above, this paper also adds to the growing body of work concerned with a task-based approach to defining jobs, human capital, and the degree of (mis)match between them (e.g., Macaluso and Borovičková (2024)). In particular, Guvenen et al. (2020) and Lise and Postel-Vinay (2020) use similar concepts of skill distance, though are more concentrated on carefully accounting for the dynamics of skill accumulation in various dimensions and the implication of these distinct skill paths for skill mismatch and resulting productivity, which is not the main focus of this paper. Both of their models imply meaningful and persistent wage penalties for skill mismatch. This is consistent with some of the empirical patterns I observe but contrasts with the lack of wage growth penalty (and in some cases wage growth premium) I find for higher levels of underqualification. This paper is also closely related to Blair, Debroy, and Heck (2021), which explores the impact of educational credentials on a worker's ability to make larger transitions. Blair et al. conclude that having a bachelor's degree makes it easier to move into jobs one is more underqualified for, a result I confirm here. While they use a cross-sectional sample of job transitions, I build upon their work by exploiting longitudinal data to capture longer-term transition patterns and outcomes as well as by adding risk preferences as a source of variation in the kinds of transitions workers make.

Finally, I provide new empirical evidence on the relationship between risk preferences, the types of transitions workers make, and wage growth, which motivate the inclusion of heterogeneous risk preferences in a model of worker mobility decisions. This presents, to my knowledge, the first such evidence on the relation between risk aversion and the kinds of transitions workers make (in terms of similarity to one's current job and wage changes). The closest existing empirical work is Huizen and Alessie (2019), which explores the impact of risk tolerance on binary worker mobility. The authors confirm that there is almost no other research in this area, pointing to Argaw, Maier, and Skriabikova (2017), which uses the German Socio-Economic Panel Survey to investigate the relation between risk attitudes and job mobility, as the only other known example. Huizen and Alessi also offer an excellent review of adjacent research on the role of risk aversion in labor market outcomes, including in the context of education and occupational choices, migration decisions, entrepreneurship, the behavior of unemployed work seekers, and wage growth, which I will not reproduce here.

In terms of theory, risk aversion tends to be assumed constant across all workers, or else absent altogether, presumably for analytical tractability. Exceptions include an early model of job search due to Pissarides that incorporates constant risk aversion, which generates a wage premium for occupations with higher wage variance (Pissarides 1974). In a similar vein, Cozzi (2012) uses a model incorporating heterogeneous risk tolerance and income risk in an attempt to match observed wealth inequality in U.S. data. Perhaps the most relevant theoretical work is Chade and Lindenlaub (2022), which presents a model of job matching with risk-averse agents and risky up-front skill investment and uses it to decompose rising U.S. wage inequality into components due to risk, heterogeneity, and technology. However, risk is still assumed to be constant across individuals in this model, and the environment and mechanisms are quite different from the framework presented here, in which risk preferences influence the *size* of the transitions that workers target.

Section 2 presents the data and measurement approaches used in the empirical analysis. Section 3 presents the main empirical findings. Section 4 presents the model and estimation results, with counterfactual exercises. Section 5 concludes.

2 Data and measurement

Sections 2.1 through 2.3 describe the data and methodology underlying the measures of risk tolerance and skill distance used throughout the paper. Sections 2.4 and 2.5 present an overview of the skill distance and dynamics of job transitions in the sample, showing that large occupational transitions are rare and workers do not tend to return to previously-held occupations after switching.

2.1 Data

Data on job transitions is constructed using labor market histories for a sample of roughly 9,000 individuals from the 1997 cohort of the National Longitudinal Survey of Youth (NLSY). This is the second cohort of the well-known NLSY survey, which tracks a nationally representative sample of U.S. workers and is described in detail in many earlier papers, e.g., Light (2005). Respondents range from ages 14 to 18 years old at the start of the survey, and are surveyed at one- or two-year intervals from that point forward, providing detailed weekly employment and wage histories. The NLSY also contains a rich set of variables on worker demographics, educational background, personality, and attitudes, including direct measures of worker general ability (as measured by ASVAB scores) and risk aversion.

I use the 1997 cohort for the primary analysis in order to avoid data quality issues identified in early rounds of the 1979 survey, as well as to simplify occupational classification. [4] However, I confirm that patterns are robust to the inclusion of the 1979 cohort, and in fact that patterns for this cohort are strikingly similar to those of the younger cohort (see Appendix B).

The main unit of analysis throughout is job transitions, where a transition is identified as a change in the worker's primary employer. [5] I apply standard restrictions to the sample of transitions by (i) limiting the set of job spells to those that start after the respondent earned their highest degree, (ii) limiting the sample to jobs averaging at least 20 hours per week and lasting at least four weeks, and (iii) excluding military jobs and self-employment

4. Training data in the NLSY79 are incomplete prior to 1988, as discussed in e.g. Kaymak (2014). Additionally, occupations are classified using 1970 Census codes before 2000, but switch to 1990 Census coding thereafter, complicating the mapping of occupations to O*NET skills.

5. Because, in the NLSY, job spell information is gathered by asking about the employer, not the job, employer and job transitions are not generally distinguishable.

(following, e.g., Farber and Gibbons (1996)). Table 1 presents summary statistics for the resulting sample of job transitions. As can be seen from the table, job transitions are a relatively rare occurrence—the median worker has made only four job transitions as of the last survey round. Additionally, the majority of transitions are among workers with less than a college degree, who also make up a majority of the worker sample. About a quarter of transitions are involuntary, and while transitions result in small gains in wages and job satisfaction on average, variance in these outcomes is substantial. In other words, transitions appear to be risky in terms of realized changes in wage and job satisfaction.

Table 1: Summary Statistics for Job Transitions

Variable	Category	Min	Mean	Std Dev	Median	Max
Ability (AFQT)		0.00	32.54	29.53	25.90	100.00
Age at Transition		14.00	26.36	5.74	25.00	42.00
Education Level	Less than HS		10.60			
	HS graduate		69.73			
	Some college		4.71			
	College graduate		11.97			
	More than college		2.99			
Race or Ethnicity	Black		28.94			
	Hispanic		20.75			
	Other		0.90			
	White (Non-Hispanic)		49.41			
Risk Tolerance		0.00	5.78	2.67	5.00	10.00
Male			0.55			
Number of Transitions per R[1]		1.00	5.02	3.83	4.0	30.00
Total Work Experience (wks)[2]		5	357.59	255.29	296.00	1118
Transition Year Category	<2000		3.08			
	[2000, 2005)		27.95			
	[2005, 2010)		31.55			
	[2010, 2015)		19.02			
	>2015		18.39			
Spell Length (wks)[2]		5	70.45	96.13	35.00	1118
Involuntary Departure			0.28			
Unemp. or OOLF Between Jobs			0.53			
Length Non-work Between Jobs (wks)		0	16.91	43.87	0.00	211
Change in Real Hourly Pay		-7.05	0.48	3.11	0.26	10.44
Change in Job Satisfaction		-4.00	0.43	1.62	0.00	4.00
Transition to Same Occupation			0.17			
Skill Distance of Transition		0.00	2.94	1.31	2.84	8.58
N=33,848						

[1] Cumulative total number of job transitions, for workers with at least one transition observed in the sample.

[2] Total work experience and spell length reflect the accumulated work experience at the time of transition and the spell length in the job preceding the transition, respectively.

Data from the Occupational Information Network ("O*NET") furnishes skill requirements for each three-digit occupation code in the sample. O*NET is a database maintained by the US Department of Labor that offers detailed information on the skills, activities, and educational requirements of approximately 1,000 occupational categories. The skill requirements of each occupation are captured by skill requirement ratings (from one to five) in 30 skill components, as assessed by expert occupational analysts (Tsacoumis and Willison 2010). [6]

2.2 Risk Attitudes in the NLSY

The measure of heterogeneous risk preferences used throughout the analysis is taken directly from the NLSY. Specifically, all NLSY97 respondents were asked to assess their level of risk tolerance on a 0-10 scale with the following question:

> *Are you generally a person who is fully prepared to take risks or do you try to avoid taking risks? Rate yourself from 0 to 10, where 0 means "unwilling to take any risks" and 10 means "fully prepared to take risks."*

Each respondent answered the question at most once, either in survey year 2010 or 2011. Risk tolerance is roughly normally distributed across the sample, with the distribution centered around five and with a standard deviation of about 2.6, as shown in Table 1. In other words, there is substantial variation in risk tolerance among respondents.

Although this risk attitudes scale is self-assessed and not incentivized, existing research demonstrates that the risk measures in the NLSY appear to accurately reflect individuals' true preferences, in the sense that they are predictive of risky behaviors such as entrepreneurship and divorce (Chekmasova (2020) and Light and Ahn (2010)). More broadly, research has shown that survey-elicited risk measures align well with incentivized lottery choices and predict real-world behaviors (Dohmen et al. (2011) and Falk et al. (2015)).

2.3 Measuring skill distance and direction

Similar to approaches in Guvenen et al. (2020) and Lise and Postel-Vinay (2020), and Blair, Debroy, and Heck (2021), I use O*NET data to define the skill requirements of each job as identified by its three-digit occupation code. Workers' skill bundles are then dynamically constructed based on their full labor market histories up to that point, such that at any given time t, a worker's current skill level for any given skill component k can be calculated as follows:

$$S_{k,t} = \begin{cases} S_{k,T} + (S_{j'} - S_{k,T})\left(1 - e^{-r_u \cdot (t-T)}\right), & \text{if } S_{j'} > S_{k,T}, \\ S_{k,T} + (S_{j'} - S_{k,T})\left(1 - e^{-r_d \cdot (t-T)}\right), & \text{if } S_{j'} < S_{k,T}, \\ S_{k,T}, & \text{if } S_{j'} = S_{k,T} \end{cases}$$

6. Skill ratings are merged into the NLSY work history data using a crosswalk between Census and SOC codes, as found on the Census website: https://www.census.gov/topics/employment/industry-occupation/guidance/code-lists.html.

where $S_{i,T}$ denotes the worker's skill level in skill i at the time T that they departed from their prior job, $S_{i,j'}$ denotes the required skill level in skill i for their current job j', identified from O*NET ratings, and r_u and r_d represent the rate of skill updating and skill depreciation, respectively. [7]

Intuitively, this equation captures the gradual adjustment of the worker's skills to those required by the job. Skills in which the worker is initially underskilled will adjust upward until they meet the new job's requirement, while skills in which the job's requirement is lower than the worker's starting level will depreciate over the course of the worker's tenure in the destination job.

With worker skill bundles and occupational skill requirements thus specified, I define the **absolute skill distance** of an occupational transition for worker i from job j to j' as the Euclidean distance between the worker's vector of current skills at the time they leave their source job and the vector of skill requirements in their destination job, as follows:

$$\text{Absolute Skill Distance} = \sqrt{\sum_{k=1}^{N} \left(S_{k,j'} - S_{k,i,T}\right)^2}$$

Where $S_{k,i,T}$ captures the worker's level of skill k at time T of transition, and the sum is taken over the 35 job skills identified in the O*NET database.

To capture the **direction** of transitions—i.e., whether they reflect moves up or down the skill ladder, in aggregate—I further decompose skill distance into components in which the worker is underskilled or overskilled. In particular, define underskill distance:

$$\text{Underskill} = \sqrt{\sum_{k=1}^{N} \mathbb{1}\left[S_{k,j'} > S_{k,i,T}\right] \left(S_{k,j'} - S_{k,i,T}\right)^2}$$

as the sum of skill distances for *only the skill components in which the worker is underskilled*. Overskill distance is defined analogously.

The difference between these identifies the worker's relative skill deficit, in terms of their current skill bundle, for the job they are transitioning into:

$$\text{Relative Skill Distance} = \text{Underskill} - \text{Overskill}$$

where positive values indicate that the worker is relatively underskilled for the destination job, while negative values indicate they are relatively overskilled. Broadly speaking, relative

7. As estimated in. e.g., Lise and Postel-Vinay (2020) and Dinerstein, Megalokonomou, and Yannelis (2022), updating and depreciation (r_u and r_d) are assumed to be asymmetrical, with skill acquisition happening much faster than depreciation. In particular, for the empirical analyses, the skill updating rate is set to $r_u = 0.11552$, which reflects the idea that skills update quickly to meet new job requirements. The Skill depreciation rate is set to $r_d = 0.00444$, consistent with depreciation rate of $\sim$5% as estimated in Dinerstein, Megalokonomou, and Yannelis (2022).

skill distance captures the extent to which the worker is moving up the skill ladder, in aggregate.

To build intuition, Table 2 provides illustrative examples of job transitions and their associated distances. Assume for these examples that each worker's skills have completely adjusted to their source job's skill requirements, so the worker's skill bundle is identical to the source job's required skill bundle.

Transition Example 1: Small absolute and relative distance, upward move. Ben resigned in disgrace from his job as a public auditor due to a minor bribery scandal, but nevertheless managed to leverage his accounting skills to land a role as the financial manager of a charitable trust for a large candy company. While both jobs have a similar skill portfolio, the financial manager job requires slightly higher levels of many skills, especially management-related ones such as Complex Problem Solving and Monitoring. At the same time, there are a few, more execution-oriented, skills for which the auditor role has higher requirements (e.g., Math and Writing). This results in a small absolute skill distance (less than 25th percentile), the majority of which is underskill, as well as a moderate and positive relative skill distance.

Transition Example 2: Larger absolute and relative distance, upward move. Andy was working as a shoeshiner in City Hall while awaiting his rock band's "big break," but networked his way into a job as a personal assistant to a bureaucratic employee, helping her launch a campaign for public office. These jobs require very different skill sets, and, in terms of direction, being a personal assistant requires higher levels of most skills. This results in a moderately large absolute skill distance (about median), the majority of which is underskill, as well as a large and positive (about 75th percentile) relative skill distance.

Transition Example 3: Large absolute distance with smaller relative distance, downward move. Ann, a nurse, had grown tired of acquaintances and even strangers soliciting her medical advice, often with upsetting pictures. So, when the opportunity arose to serve as the public relations manager for her city's public health department, she happily accepted. These jobs are quite different and require substantially different skill sets, but it isn't immediately clear which job is higher-skill. This is reflected in the skill distance measures—the absolute skill difference between the two occupations is large (above median), but this is driven by both underskill (e.g., PR management requires higher levels of sales-type skills such as Negotiation than nursing) and overskill (e.g., nursing requires higher skills in Science than PR management). The result is a negative, though small, relative skill distance—nursing has a slightly higher skill requirement than PR management, in aggregate.

Table 2: Illustrative Job Transition Examples

Name	Source Occupation	Destination Occupation	Absolute Skill Dist.	Underskill	Overskill	Relative Skill Dist.
(1) Ben	Auditor *(800)*	Financial Manager *(120)*	1.577	1.324	0.858	0.466
(2) Andy	Shoeshiner[1] *(4520)*	Personal Assistant[2] *(5700)*	2.498	2.393	0.715	1.678
(3) Ann	Nurse *(3130)*	PR Manager *(60)*	2.917	1.679	2.385	-0.707

2002 Census codes corresponding to each occupation in parentheses.

[1] Shoeshiner is mapped to Census code 4520: Miscellaneous personal appearance workers.

[2] Personal Assistant is mapped to Census code 5700: Secretaries and administrative assistants.

2.4 Distribution of skill distance

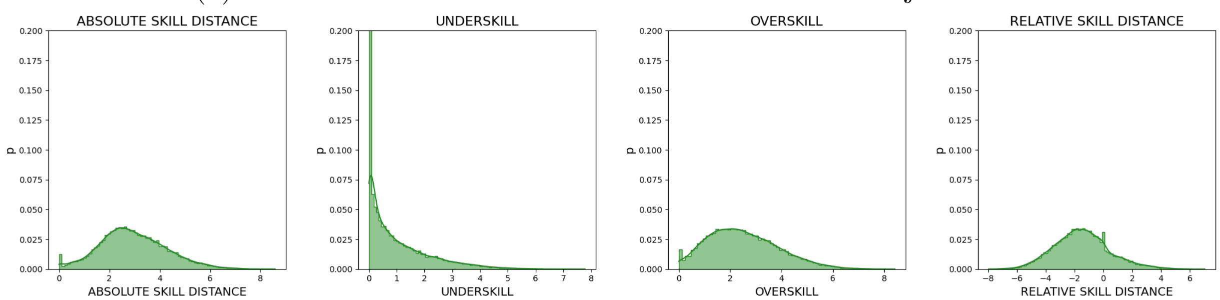
Figure 1 shows the sample distribution of each skill distance measure for (a) the distance between the worker's skill bundle at the time of transition and the skill requirements of their destination job, and (b) the distance between the source job and destination job skill requirements. Because skills are assumed to update faster than they depreciate, workers tend to be more overskilled than underskilled when considering their full labor market histories, though this is not by construction (e.g., this would not be the case if workers moved into progressively higher-skill jobs throughout their careers on average—see Appendix A.1 for simulated distributions with random transitions for comparison). On the other hand, when comparing the skill requirements of source and destination jobs, underskill and overskill are roughly symmetric, resulting in a distribution of relative skill distance that is roughly centered at zero. In other words, **workers are about as likely to move down the skill ladder as up the skill ladder on any given transition**, relative to their source job, suggesting that workers may struggle to target strictly higher-skill jobs (and this remains true when restricting the sample to only voluntary transitions—see Appendix A.2 for details).

The distributions are generally right-skewed, reflecting the fact that larger transitions are relatively rare. In particular, when using the worker's skill bundle based on their full job history, large underskill is quite rare, and in fact the modal transition has zero underskill distance. This results in an asymmetric distribution of relative skill distance, in which the majority of transitions have negative relative distance (workers have a higher aggregate skill level than the requirements of the jobs to which they are transitioning). Additionally, when comparing source and destination job skills only, we see that the modal transition is zero-distance; that is, the modal transition is to a job in the same occupation with a different employer.

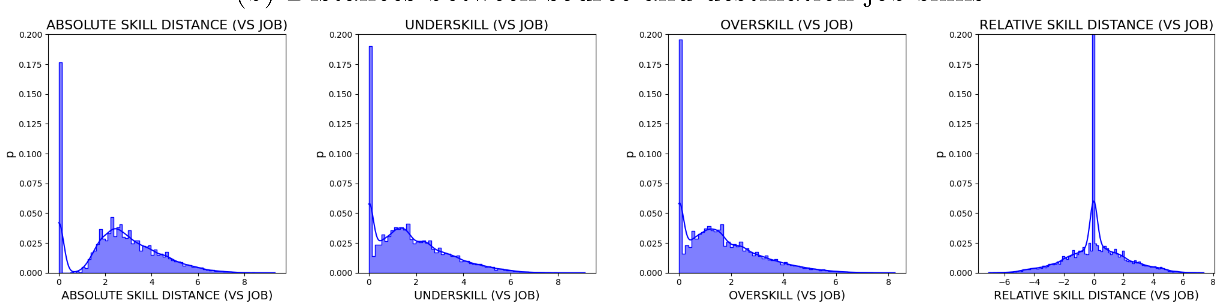
The empirical analyses shown throughout the remainder of the paper use skill distance based on the worker's skill bundle, incorporating their full work history as laid out in section 2.3. Since skills are assumed to appreciate faster than they depreciate, this measure provides a rough upper bound on each worker's skills, while the distance between source and destination jobs can be thought of as a lower bound (as it assumes workers possess only the skills acquired in their most recent job). Therefore, estimates of the effect of underskill using the first measure are likely somewhat conservative. In practice, however, results are quite similar when using skill distances between the source and destination jobs (see Appendix D).

Figure 1: Skill distances of job transitions

(a) Distances between worker skills and destination job skills



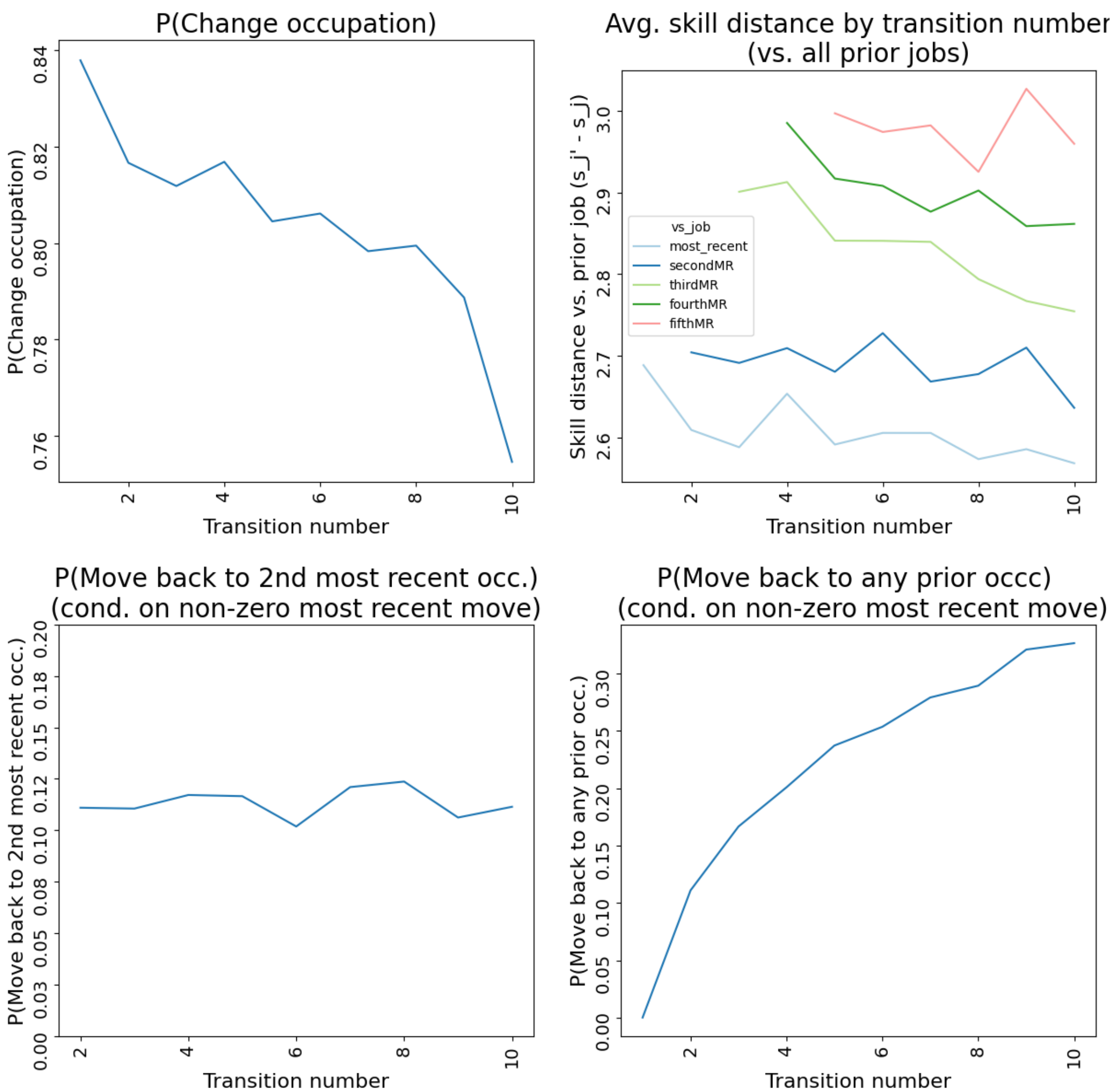
(b) Distances between source and destination job skills



2.5 Transition dynamics

Figure 2 documents the dynamics of transitions as workers as workers progress in their careers. Figures reflect averages across all workers' nth job transitions, for up to the first ten transitions of each worker's career. Thus, each point on the x-axis reflects the sample average *conditional on having made that many transitions*. The top left figure shows that workers are less likely to change occupations as they progress in their careers, with the probability of occupation switching dropping from 84% on a worker's first transition to 76% on a worker's tenth transition. The top right figure shows that the absolute skill distance between a worker's destination job and their nth most recent job at any given transition is increasing in n—in other words, workers tend to move monotonically further away from their older jobs in terms of skills, on average. The bottom two figures show that it is relatively rare for workers to return to prior occupations after making a switch. In particular, the probability of returning to the $n-1$th, conditional on switching occupations at the nth transition, is only about 10%, regardless of transition number. Additionally, while the probability of moving back to *any* previously-held occupation is monotonically increasing (since a higher transition number means a larger set of occupations to potentially move back to), it never exceeds 35%, and is only about 20% for the fourth transition (the maximum for the median worker in the sample).

Figure 2: Transition dynamics



3 Empirical Patterns

The following sections describe the empirical patterns that motivate the model of occupational transition decisions in Section 4.

Sections 3.1 and 3.2 present an empirical puzzle: as shown in 3.1, skill mismatch appears to matter—large underskill distances are rare, and being underskilled predicts employer training and wage *level* penalties compared to workers in the same occupation—but as shown in 3.2, greater skill mismatch is associated with better short- and long-term transition outcomes *as long as the direction of the move is positive (moving up the skill ladder).* In other words, in addition to yielding better long-term outcomes, being underskilled actually carries immediate wage *growth* premiums compared to transitions in which the worker is closely matched or overskilled compared to their destination job. This raises the question: if moving up the skill ladder is so beneficial, and does not carry short-term wage *growth* penalties, why aren't more workers making these steep transitions?

Section 3.3 offers risk as a potential explanation. Specifically, workers may be hesitant to make larger transitions because they are riskier. I hypothesize that higher absolute skill distance is associated with higher risk due to information frictions—workers are well-informed about jobs that are similar to their own, but know increasingly less about jobs that are further afield. This makes larger moves risky because workers don't necessarily know whether they are moving into overall higher-skill (and thus likely higher-quality) jobs or lower-skill ones. While it may at first seem implausible that workers don't know ex-ante whether they are moving up or down the skill ladder, recall from Figure 1 that workers are about as likely to move down the skill ladder as up compared to their source job, suggesting workers are not able to precisely target higher-skill jobs. Further, the multi-dimensionality of skills makes aggregate comparisons non-trivial, particularly for jobs that are very different (e.g., Ann's transition from nurse to PR manager as shown in Table 2 is a downward move, but this is not obvious). Supporting this hypothesis, section 3.3 demonstrates that higher risk tolerance is associated with both transition probability and the absolute skill distance of transitions, and confirms that higher absolute skill distance is indeed associated with higher risk, in the form of higher variance in realized job quality.

3.1 Worker-job skill match matters

This section presents results that are consistent with models of skill mismatch in which task-specific skills are important for productivity. Specifically, larger job transitions, and particularly transitions with large underskill distance, are relatively rare, and underskill is predictive of training receipt in the destination job, suggesting that workers and employers care about skill match, and underskill in particular. Further, absolute skill distance is associated with wage growth penalties and negative transition conditions such as involuntary departure and longer non-work spells between jobs, suggesting that workers may tend to be "pushed" rather than "pulled" into making larger absolute skill distance moves.

First, large transitions are rare. As shown in figure 1, all skill distance distributions are right-skewed, and the modal transition is within occupations (i.e., the worker moves into the same occupation with a different employer). [8] This is consistent with an environment in which it is difficult or costly to be hired into or perform jobs that require very different skills from your current skill bundle. Further, relative skill distance is less than zero on average—i.e., workers are more likely to move to jobs they are relatively overskilled, rather than underskilled, for. While this is not surprising given that skills are assumed to update faster than they depreciate, it is not fully by construction [9], and this also could indicate a state of the world in which employers care about skills and are reluctant to hire workers with insufficient skills.

Secondly, absolute skill distance is associated with a higher incidence of employer-provided training receipt in the first year of the new job, and this is driven completely by underskill. Specifically, as shown in Table 3, an increase of one standard deviation in underskill increases the probability of receiving employer-provided training in the first year of the destination job by about 1 percentage point, or about a 20% increase from the sample average of 4.2%. This suggests that workers must adjust their skills when their current level of a given skill is too low to meet the requirements of the job, sometimes with assistance from employers. This relationship holds even after controlling for a broad array of destination job characteristics such as wages, hours, and occupation and industry categories, which implies that the observed training provision is truly driven, at least in part, by skill mismatch, rather than job complexity or job quality.

Additionally, to the extent that skill mismatch negatively impacts productivity, we should expect workers with skill mismatch to earn less than their counterparts with well-matched skills, at least initially. The data confirms this. As shown in Table 4, a worker's real wage *level* in the first year of a job, controlling for occupation and industry fixed effects, is negatively impacted by skill mismatch. That is, given two workers in the first year of a new job in the same occupation, the one with skills that are a closer match to the occupation's skill requirements will earn more. This is again driven more by underskill: an increase of one standard deviation in underskill is associated with a 4.7% lower real wage rate in the first year of the new job, relative to other workers in the same occupation. Interestingly, however, overskill also incurs a small but significant wage level penalty.

Finally, there is a meaningful relationship between worker and transition characteristics and skill distance. In particular, general human capital (in the form of both education

8. Note that within-occupation transitions need not, and generally will not, have zero skill distance between the worker's skill bundle and the destination job's skill requirements, as the worker likely has accumulated other skills from prior jobs that have not fully depreciated.

9. This would not be true if, e.g., workers always moved into jobs with higher skill requirements in every skill component relative to their prior job.

Table 3: Any employer-provided training in first year of new job

	(1)	(2)	(3)
Absolute skill distance	0.004***		
	(0.001)		
Underskill		0.008***	
		(0.002)	
Overskill		0.002	
		(0.001)	
Relative skill distance			0.004**
			(0.002)
Controls:			
Demographics	✓	✓	✓
Job & transition vars.	✓	✓	✓
Year, occupation & industry FEs	✓	✓	✓
Outcome variable:			
Mean	0.042	0.042	0.042
Std. Deviation	0.200	0.200	0.200
R2	0.065	0.066	0.065
N	33483.000	33483.000	33483.000

Robust standard errors in parentheses (* p<0.1, ** p<0.05, ***p<0.01)

Reflects a binary indicator for whether the respondent reported any employer-provided training in the first year of their new job, regressed on skill distance and controls for worker demographics, characteristics of the source and destination job and of the transition, year fixed effects, and fixed effects for the occupation and industry of the new job.

and general ability as measured by ASVAB scores) appears to be positively associated with skill distance, suggesting that broader aptitude may be somewhat substitutable for specific skills in some cases. In particular, as shown in Table 5, having a college degree is strongly associated with underskill and relative skill distance, consistent with the idea that higher education may mitigate skill mismatch costs (e.g., by allowing workers to learn new skills more quickly). Additionally, there is a positive relationship between more negative transition conditions (involuntary departures, a higher unemployment rate at the time of transition) and larger transitions in terms of absolute skill distance. This could suggest that workers would generally prefer to move to jobs that are a good fit with their skills, and are more likely to make bigger moves under duress or when a close skill match is difficult to find.

Table 4: Log wage level vs. occupation mean in first year of new job

	(1)	(2)	(3)
Absolute skill distance	-0.029***		
	(0.002)		
Underskill		-0.047***	
		(0.002)	
Overskill		-0.012***	
		(0.002)	
Relative skill distance			-0.022***
			(0.002)
Controls:			
Demographics	✓	✓	✓
Job & transition vars.	✓	✓	✓
Year, occupation, & industry FEs	✓	✓	✓
Log wage level:			
Mean	6.277	6.277	6.277
Std. Deviation	0.493	0.493	0.493
R2	0.565	0.569	0.563
N	32658	32658	32658

Robust standard errors in parentheses (* $p<0.1$, ** $p<0.05$, *** $p<0.01$)

Reflects logged real wage level in the worker's first year of the job regressed on skill distance and controls for worker demographics, characteristics of the job and of the transition into the job, year fixed effects, and fixed effects for the occupation and industry of the job.

Table 5: Correlates of skill distance

	Absolute skill distance	Underskill	Overskill	Relative skill distance
Demographics:				
Ability (ASVAB)	0.158***	0.112***	0.110***	-0.012
	(0.026)	(0.026)	(0.026)	(0.026)
High school grad	0.183***	0.123***	0.134***	-0.022
	(0.018)	(0.018)	(0.018)	(0.018)
Some college	0.202***	0.148***	0.142***	-0.013
	(0.033)	(0.031)	(0.033)	(0.032)
College grad	0.185***	0.291***	0.059**	0.129***
	(0.027)	(0.027)	(0.026)	(0.026)
More than college	-0.080*	0.137***	-0.131***	0.173***
	(0.041)	(0.037)	(0.040)	(0.036)
Age	0.114***	-0.147***	0.198***	-0.226***
	(0.011)	(0.010)	(0.010)	(0.010)
Age^2	-0.002***	0.002***	-0.003***	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)
Male	0.260***	0.085***	0.228***	-0.111***
	(0.011)	(0.011)	(0.011)	(0.011)
Black	-0.043***	-0.018	-0.027**	0.008
	(0.013)	(0.013)	(0.013)	(0.013)
Hispanic	0.016	0.071***	-0.018	0.054***
	(0.015)	(0.015)	(0.015)	(0.015)
Other Race or Ethn.	-0.143**	-0.039	-0.113**	0.057
	(0.057)	(0.058)	(0.055)	(0.054)
Total experience (yrs)	0.001	-0.011***	0.007***	-0.011***
	(0.002)	(0.002)	(0.002)	(0.002)
Job and transition variables:				
Real wage (old job)	-0.163***	-0.068***	-0.130***	0.052***
	(0.014)	(0.014)	(0.014)	(0.014)
Hrs per wk (old job)	-0.000	-0.005***	0.002***	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
Involuntary depart.	0.032**	-0.088***	0.082***	-0.110***
	(0.013)	(0.012)	(0.013)	(0.013)
Time between jobs (wks)	0.000***	0.001***	0.000	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Training between jobs	0.012	-0.003	0.013	-0.011
	(0.034)	(0.037)	(0.034)	(0.036)
Unemployment rate	0.008**	0.000	0.005	-0.003
	(0.004)	(0.004)	(0.004)	(0.004)
R2	0.034	0.046	0.051	0.062
N	32707	32707	32707	32707

Robust standard errors in parentheses (* $p<0.1$, ** $p<0.05$, *** $p<0.01$)

Reflects the skill distance of each observed job transition regressed on worker demographic variables and characteristics of the source job and of the transition.

3.2 Job skill level matters more for transition outcomes

Although skill match is important, the skill *level* of the destination job appears to be more important for determining the outcome of job transitions. Conditional on making a job transition, higher levels of underskill and relative skill distance are associated with better transition outcomes, both immediately and in the long term. This holds true for wages as well as other measures of job quality such as job satisfaction and tenure. Further, I find that making larger upward occupational transitions is associated with sustained wage gains and higher mid-career wages conditional on the overall number of job moves, respectively.

In other words, it appears that the optimal job ladder is short (comprised of a low number of transitions) but steep (in the sense that the higher the skill gradient of each transition, the better). While it makes sense that moving into higher-skill jobs ultimately results in higher wages, it is somewhat surprising that these benefits appear to be immediate and sustained, rather than involving an initial trade-off between human capital accumulation or learning and future wage growth.

Throughout this section, results for relative skill distance, which captures the extent to which the job requires higher aggregate skills compared to the worker's current skill bundle, are highlighted. Relative skill distance is a parsimonious indicator of how far up or down the skill ladder the worker is moving. Results for underskill and overskill are also shown throughout to provide intuition for how these are each contributing to the total effect.

As shown in Table 6, higher levels of relative skill distance are strongly positively associated with the wage change upon transition. Specifically, an increase of one standard deviation in relative skill distance is associated with wage growth that is 5.7 percentage points higher than for the average transition, almost doubling the sample mean of roughly 6.6%. This is in stark contrast to the large and significant wage growth penalty for absolute skill distance, which is driven by overskill. Clearly, the skill *direction* of the move is an important dimension to consider when analyzing occupational transitions, as absolute distance alone fails to capture this divergence. The immediate and marked wage boost from making a larger move into a job one is relatively underskilled for is surprising in the context of a job-specific skills model, many of which would predict at least a temporary wage growth penalty. Instead, it seems that the productivity gains from these types of larger upward jumps overshadow any skill mismatch costs.

This could be consistent with positive selection on unobservable worker or match characteristics, or with a basic job ladder model in which output is mostly driven by job quality, rather than attributes of the particular worker-job match. Indeed, selection is almost surely part of the story. As shown in Table5, larger relative skill distance is associated with positive observable characteristics such as higher education (college degree or higher) and voluntary departures. However, the wage growth effects persist after controlling for all standard observables (as shown in Table 6, and even after including individual fixed effects (as shown in

Appendix C). This suggests that the wage growth premium for steeper upward transitions is not entirely due to the selection of workers with higher unobserved productivity; rather, there appears to be some degree of luck involved in determining who moves up the skill ladder.

Table 6: Wage growth from transitions

	(1)	(2)	(3)
Absolute skill distance	-0.026***		
	(0.002)		
Underskill		0.031***	
		(0.002)	
Overskill		-0.042***	
		(0.002)	
Relative skill distance			0.057***
			(0.002)
Controls:			
Demographics	✓	✓	✓
Job & transition vars.	✓	✓	✓
Year FEs	✓	✓	✓
Change in log wage:			
Mean	0.066	0.066	0.066
Std. Deviation	0.419	0.419	0.419
R2	0.256	0.270	0.270
N	32031	32031	32031

Robust standard errors in parentheses (* p<0.1, ** p<0.05, ***p<0.01)

Reflects the change in logged real wage level from the end of the worker's old job to the start of their new job regressed on skill distance and controls for worker demographics, characteristics of the source and destination jobs and of the transition, and transition year fixed effects.

In addition to higher pay, higher relative skill distance is positively associated with changes in job satisfaction as well as tenure in the destination job, as shown in 7. In particular, a one standard deviation increase in relative skill distance is associated with an almost 25% larger increase in job satisfaction compared to the sample mean, as well as about three months of additional tenure in the new job on average. These patterns reinforce the idea that steep upward transitions result in higher-quality or more productive matches.

In particular, it is interesting to note that higher relative skill distance is associated with larger gains in job satisfaction *even after controlling for wages* (and other job attributes). One possible explanation of this pattern is that, as workers gain labor market experience, they learn private information about attributes not observable in the data (and potentially not observable to employers) that impact their productivity in different occupations (e.g., preferences over non-wage job attributes), which they use to target better-matched jobs. However, the fact that job satisfaction, job skill level, and wages tend to co-move makes the fact that so many workers make downward transitions more difficult to rationalize, as it does not appear to be the case that workers are sacrificing wages for non-wage amenities (which should presumably show up in job satisfaction). This result further indicates that workers may struggle to understand which jobs are higher-skill in aggregate or to effectively target these jobs when searching.

Table 7: Other transition outcomes

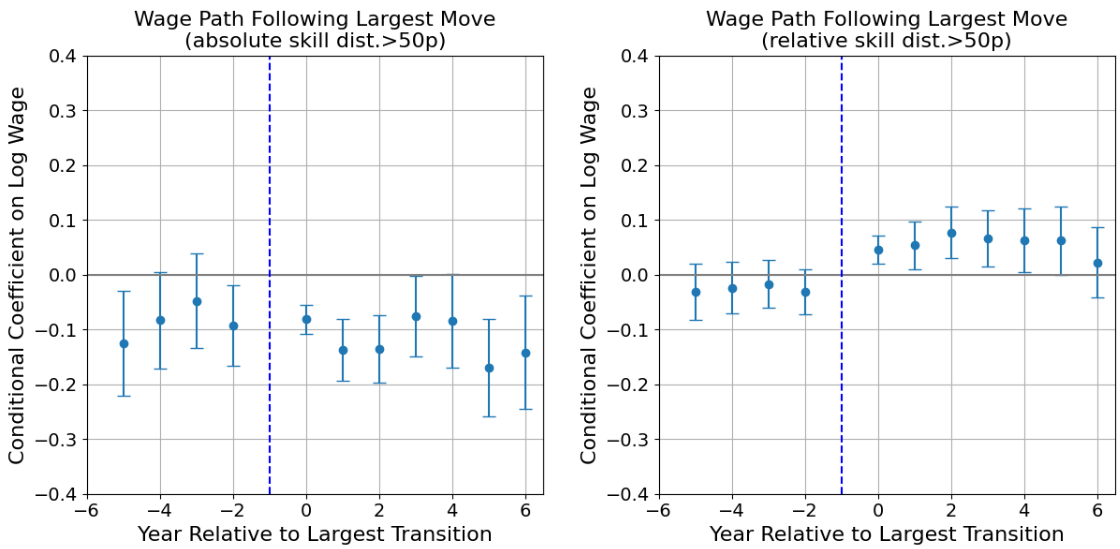
	Change in Job Sat.			Tenure in New Job		
	(1)	(2)	(3)	(4)	(5)	(6)
Absolute skill distance	0.009			-0.001		
	(0.008)			(0.012)		
Underskill		0.094***			0.231***	
		(0.008)			(0.014)	
Overskill		-0.029***			-0.097***	
		(0.008)			(0.011)	
Relative skill distance			0.091***			0.245***
			(0.008)			(0.013)
Controls:						
Demographics	✓	✓	✓	✓	✓	✓
Job & transition vars.	✓	✓	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓	✓	✓
Outcome variable:						
Mean	0.401	0.401	0.401	1.883	1.883	1.883
Std. Deviation	1.459	1.459	1.459	2.681	2.681	2.681
R2	0.025	0.029	0.028	0.050	0.068	0.065
N	32707	32707	32707	28250	28250	28250

Robust standard errors in parentheses (* $p<0.1$, ** $p<0.05$, *** $p<0.01$)

Reflects the job satisfaction from the end of the worker's old job to the start of their new job (columns (1)-(3)) or the tenure in years in the new job (columns (4)-(6)) regressed on skill distance and controls for worker demographics, characteristics of the source and destination jobs and of the transition, and transition year fixed effects. The sample for tenure regressions is limited to transitions in which the destination job spell is complete (i.e., not truncated by the end of the survey).

Turning to longer-term post-transition outcomes, the wage benefits of moving up the skill ladder are immediate and sustained, based on wage paths pre- and post-transition (using each respondent's *largest* transition in terms of absolute skill distance, compared to non-movers in the same periods), as shown in Figure 3. While making an above-median transition in terms of *absolute* skill distance is associated with wage stagnation or even a slight wage penalty relative to non-movers, making an above-median transition in terms of *relative* skill distance is associated with immediate and continued wage gains. It is also interesting to note that workers making larger upward transitions do not appear to be positively selected in terms of pre-transition wages or wage growth.

Figure 3: Wage paths following transitions



Finally, Table 8 presents the results of a Mincer-style wage decomposition of age 35 wages in the sample (roughly the highest age that all survey respondents have reached by the most recent available survey round). Making larger upward transitions on average significantly predicts mid-career wage levels in the sample, even after controlling for starting wage, total work experience, the total number of job transitions the worker has made, and a rich set of controls. In particular, a one-unit increase in the relative skill distance of the worker's *average* transition is associated with the same wage gain as over a year of additional work experience. On the other hand, there is a negative relationship between the raw count of job transitions and wages, suggesting that fewer, but steeper, upward moves (relative to the worker's current skills) are associated with the best wage trajectories.

Taken together these patterns suggest that, conditional on being able to make such a move, the job or match quality effects of moving into a job one is relatively underskilled for outweigh the effects of skill mismatch. Which raises the question: who is making these steep upward transitions, and why aren't more workers making similar transitions (or at least moving strictly upward)? As discussed in Section 3.1, there does appear to be some degree of selection. Workers with more education (specifically, at least a college degree) tend to make larger upward moves, while involuntary transitions and higher unemployment are associated with downward moves. This could align with either selection (lower-quality

Table 8: Log wage level at age 35

	(1)	(2)	(3)	(4)
Cumulative avg., absolute skill dist.	-0.010			
	(0.007)			
Cumulative avg., underskill		0.059***		
		(0.011)		
Cumulative avg., overskill			-0.030***	
			(0.007)	
Cumulative avg., relative skill dist.				0.043***
				(0.006)
Real wage in first job	0.292***	0.312***	0.290***	0.299***
	(0.021)	(0.021)	(0.021)	(0.021)
Total experience (yrs)	0.037***	0.036***	0.037***	0.036***
	(0.002)	(0.002)	(0.002)	(0.002)
Total number of transitions	-0.010***	-0.007***	-0.008***	-0.005**
	(0.002)	(0.002)	(0.002)	(0.002)
Controls:				
demographics	✓	✓	✓	✓
year FEs	✓	✓	✓	✓
Log wage level at age 35:				
Mean	6.722	6.722	6.722	6.722
Std. Deviation	0.572	0.572	0.572	0.572
R2	0.358	0.363	0.361	0.366
N	3827	3827	3827	3827

Robust standard errors in parentheses (* p<0.1, ** p<0.05, ***p<0.01)

Reflects the logged real wage level of each worker at age 35 (for workers with a wage observation available) regressed on the average skill distance across all the transitions the worker has made up to age 35, along with controls for the worker's wage level in their first observed job, their total work experience, the total number of job transitions they've made, worker demographics, and year fixed effects.

workers are both more likely to be fired and less able to match with highskill jobs) or a simple job ladder in which laid-off or unemployed workers have lower reservation wages. Stepping back, the R-squared for the regressions in Table 5 (predicting skill distance) are quite low, suggesting that, while worker characteristics and the circumstances of the transition do play a meaningful role in the career moves workers choose to or are able to make, there may also be a good deal of randomness. To the extent that the degree of randomness—or risk—is correlated with the size of the transition (in terms of absolute distance), heterogeneous risk tolerance may help explain these patterns. The following section explores this idea.

3.3 Ladders or chutes: the role of risk

Given the preceding results, it is difficult to understand why more workers don't make larger upward transitions, or why so many transitions are actually *down* the skill ladder. I propose one explanation in which transitions are risky because workers have imperfect information about job skill levels ex ante, and cannot precisely target higher-skill jobs. In other words, they may be uncertain whether a particular transition would be a "ladder" (upward move) or a "chute" (downward move). Additionally, larger skill distance transitions are riskier due to higher uncertainty—workers know less about jobs that are less similar to their current work. Thus, workers may be hesitant to make larger moves not (or not only) because their skills are mismatched, but also because they are risk averse and larger transitions carry more risk. Supporting this hypothesis, I show that higher risk tolerance is associated not only with the probability of making a job transition, but also with absolute skill distance—i.e., more risk-tolerant workers make larger moves. Additionally, higher absolute distance is in fact riskier in terms of realized destination job quality.

As one might expect, higher risk tolerance is correlated with a higher probability of making *any* job transition. However, the size of the effect is relatively small. As shown in Table 9, moving from the lowest possible level of risk tolerance to the highest is associated with an increase of roughly 1.5 percentage points in the probability of making a transition, which is small relative to the sample average of about 28%. Though small, the relationship between risk tolerance and transition probability is robust to a large set of demographic and source job controls.

Beyond this relationship between risk tolerance and binary transition probability, risk tolerance also predicts the *size* of the transition. As shown in Table 10, moving from the lowest possible level of risk tolerance to the highest is associated with a significant increase in absolute skill distance—about double the effect of involuntary departure (from Table 5). There is generally not a significant relationship between risk tolerance and the other skill distance measures, which capture direction. This makes sense in a world where workers are not able to precisely identify higher-skill jobs. Indeed, this is potentially the source of the risk. While more risk-tolerant workers are more willing to move into jobs that are more different from their own, they don't seem to be able to move into strictly higher-skill jobs.

Finally, bigger skill distance moves *are*, in fact, riskier. Proxying occupation quality with the mean real wage of each occupation in the sample, Figure 4 shows that higher absolute skill distance is associated with greater variance in the change in job quality following a transition. Specifically, the dispersion of outcomes is monotonically increasing in the absolutes skill distance quartile of the transition. In other words, making a larger transition in terms of absolute skill distance can result in moves to much higher-quality jobs *or* much lower-paying jobs. Notably, this is true even when limiting the sample to voluntary transitions; while the distributions for involuntary departures are less favorable, moves to lower-quality

Table 9: Probability of any job transition in a given year

	(1)	(2)	(3)	(4)
Risk tolerance	0.014***	0.014***	0.015***	0.013***
	(0.004)	(0.004)	(0.004)	(0.004)
Controls:				
Demographics	✓	✓	✓	✓
Job vars.		✓	✓	✓
Year FEs			✓	✓
Ooccupation & industry category FEs				✓
Transition probability:				
Mean	0.280	0.280	0.280	0.280
R-squared	0.102	0.133	0.143	0.145
N	148490	148490	148490	148490

Robust standard errors in parentheses (* p<0.1, ** p<0.05, ***p<0.01)

Reflects a binary variable reflecting whether each worker made a job transition in each year in which they are observed in the data, regressed on risk tolerance (normalized to a 0 to 1 scale) and (depending on the specification) controls for worker demographics, characteristics of the worker's current job, year fixed effects, and occupation and industry fixed effects for the worker's current job.

Table 10: Skill distance and risk tolerance

	Absolute skill distance	Underskill	Overskill	Relative skill distance
Risk tolerance	0.062***	0.029	0.039*	-0.006
	(0.021)	(0.020)	(0.020)	(0.020)
Controls:				
Demographics	✓	✓	✓	✓
Job & transition vars.	✓	✓	✓	✓
Year & occupation, industry cat. FEs	✓	✓	✓	✓
R2	0.063	0.094	0.139	0.162
N	30347	30488	30488	30488

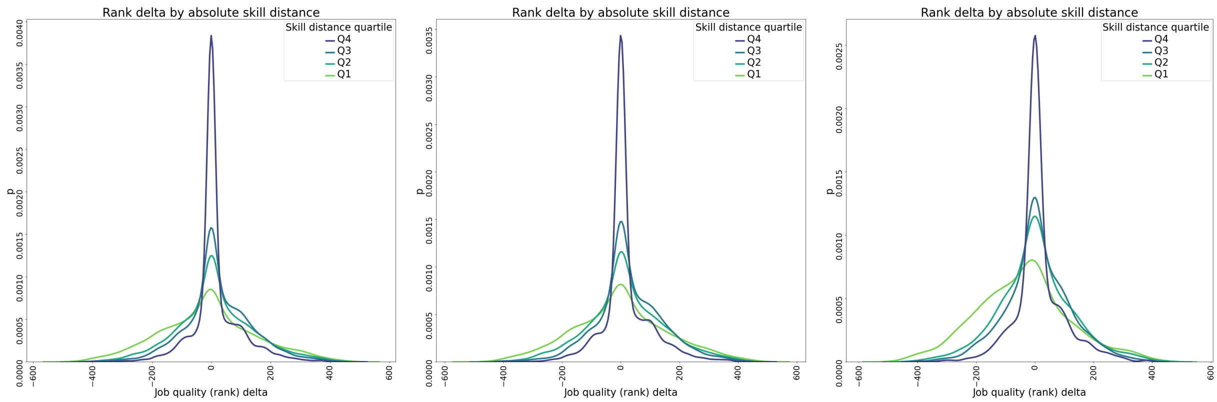
Robust standard errors in parentheses (* p<0.1, ** p<0.05, ***p<0.01)

Reflects the skill distance of each observed job transition regressed on risk tolerance (normalized to a 0 to 1 scale) and controls for worker demographics, characteristics of the worker's current job, year fixed effects, and occupation and industry fixed effects for the worker's current job.

occupations are not driven only by these involuntary transitions.

Taken all together, these patterns are consistent with a world in which big career moves

Figure 4: Change in job quality by absolute skill distance quartile



(a) All transitions (b) Voluntary transitions (c) Involuntary transitions

are risky because job skill level and quality are difficult to observe during job search, with higher uncertainty about jobs that are more distant from your current field. Due to this uncertainty, more risk-averse workers avoid making larger transitions. Thus, even though large *upward* transitions are so advantageous, we do not observe many in practice. Further, since workers are not able to perfectly observe aggregate job skill levels ex ante, we see workers making transitions both up and down the skill ladder. The next section presents a model exploring the implications of these hypothesized conditions.

4 Model

4.1 Model set-up and intuition

Workers are characterized by their education level α_i (less than college or college graduate), skill level κ_i, and heterogeneous risk aversion γ_i. Jobs are characterized by their skill requirement κ_j and job quality q_j, which is assumed to be imperfectly correlated with skill requirements (as observed in the data).

There are two periods. In period 1, workers choose a job search strategy s defined by an **absolute** skill distance range. Workers are only able to choose the absolute skill distance over which they are searching for jobs, reflecting the idea that they are uncertain about aggregate job skill levels ex-ante, and thus cannot precisely target strictly higher-skill jobs. Workers then draw a new job from a known distribution that depends on their chosen strategy s. They receive a wage in the new job determined by their education and skill levels and the new job's skill requirements and quality. Thus, workers choose a search strategy s to maximize expected utility in period 2 according to:

$$\max_{s} \mathbb{E}[u(w_{ij'}(\alpha_i, d_{ij'}, q_{j'}), \gamma)|s, \alpha_i, \kappa_i] \tag{1}$$

where $w_{ij'}$ is the wage in the destination job (j'), α_i is the worker's education level, $d_{ij'} = \kappa_{j'} - \kappa_i$ is the distance between the job's skill requirement and the worker's skill level, and $q_{j'}$ is the job's quality.

To provide intuition about the mechanisms through which skill mismatch and risk tolerance influence workers' job search decisions in this setting, the remainder of the section solves a **simplified** version of the model. The model specification used for estimation is presented in the following section.

Solution to simplified model: Start by specifying the wage function as follows:

$$w_{ij} = \beta_e \alpha_i + \beta_q \kappa_j + \beta_s(\kappa_i - \kappa_j) \tag{2}$$

Where β_e captures the effect of education on the wage level, β_q) captures the effect of job quality (assumed to be equal to skill level in this simplified version of the model) and β_s captures the effect of skill distance, or skill mismatch.

The job search strategy determines the *variance* of the distribution of skill levels from which the worker is drawing their new job. This captures the idea that workers can influence the riskiness of their job search strategy. The specification used in estimation introduces more complex distributions that approximate discontinuous skill distance ranges, reflecting the idea that workers can choose to look "closer" or "further" from their current job, but these discontinuities make a closed-form solution intractable. So, for this example specify the distribution of new job skill level $kappa_{j'}$ as a function of search strategy s as follows:

$$\kappa_{j'} \sim N(\kappa_i + ds, \sigma^2(s)) \tag{3}$$

Where κ_i is the worker's current skill level (i.e., search is centered around the worker's current skill), $d \geq 0$ is a risk premium implying that workers who choose riskier search strategies are able to (imprecisely) target somewhat higher skill jobs by shifting the center of the distribution upwards, and $\sigma^2(s)$ is the variance of the distribution, which is assumed to be monotonically increasing in s. In other words, choosing a higher level of s results in higher risk.

Finally, worker utility over wages follows a simple CARA form:

$$U(w_{ij}) = -\exp(-\gamma_i w_{ij}) \tag{4}$$

where $\gamma_i > 0$ is worker i's coefficient of absolute risk aversion.

Then, workers choose s to maximize expected utility in their new job j':

$$\max_s E[U(w_{ij'})] = -\exp\left(-\gamma E[w_{ij'}] + \tfrac{1}{2}\gamma^2 \operatorname{Var}[w_{ij'}]\right)$$

Taking the expectation of wages over the distribution of new job skill level depending on search strategy s yields expected wage:

$$E[w_{ij'}] = \beta_e \alpha_i + \beta_q \kappa_i + \beta d s \tag{5}$$

with variance: $\operatorname{Var}[w_{ij'}] = \beta^2 \sigma^2(s)$ (where $\beta = \beta_q - \beta_s$).
Substituting this into the utility function gives expected utility:

$$E[U(w_{ij'})] = -\exp\left(-\gamma(\beta_e \alpha_i + \beta_q \kappa_i + \beta d s) + \tfrac{1}{2}\gamma^2 \beta^2 \sigma^2(s)\right)$$

Collecting only the terms dependent on s into Ψ yields the following first order condition:

$$\frac{d\Psi}{ds} = -\gamma \beta d + \tfrac{1}{2}\gamma^2 \beta^2 \frac{d\sigma^2(s)}{ds} = 0$$

Rearranging terms, we can derive the following condition for the optimal search strategy:

$$\frac{1}{2}\gamma^2 \beta^2 \frac{d\sigma^2(s^*)}{ds} = \gamma \beta d \implies \frac{d\sigma^2(s^*)}{ds} = \frac{2d}{\gamma \beta}$$

The above implies that, as long as $\beta_q > \beta_s$, more risk-tolerant workers choose higher s because they are willing to accept higher variance for higher expected wages. In other words, as long as the skill mismatch penalty is sufficiently low, the wage benefits of moving up the skill ladder outweigh the wage penalty of skill mismatch, and workers will accept some degree of risk for the chance to move up the skill ladder, depending on their risk tolerance.

4.2 Estimation

The model specification used for estimation is more complex, and does not permit a closed-form solution. It includes a richer wage equation, CRRA utility, and discontinuous distributions of new job skill level that capture the idea of workers searching in absolute skill distance "ranges."

Wage determined based on worker education and skill level and job skill level and quality as follows:

$$w_i j = \beta_1 q_j + \beta_2 d_{ij} + \beta_3((1 - \alpha_i) * d_{ij}) + \beta_4(\alpha_i q_i) \tag{6}$$

where q_j is job quality, $d_{ij} = \kappa_j - \kappa_i$ captures relative skill distance, and α_i is the worker's education level. For computational tractability, skill levels and job skill requirements are reduced to uni-dimensional variables capturing aggregate skill levels. There are two education (α) groups, comprised of workers without a college degree and workers with a college degree.

Worker utility is given by:

$$U(w_{ij}) = \frac{w_{ij}^{(1-\gamma_i)}}{(1-\gamma_i)} \tag{7}$$

For estimation, workers take one of four possible values of risk aversion γ_i, determined based on their self-reported risk aversion and mapped into values ranging from 0 (no risk aversion) to 5 (highest possible risk aversion).

Workers choose one of four possible skill distance strategies ($s = 0$ to 3), where 0 represents the special case of a zero-distance move (stay in the same occupation) and 3 targets the largest absolute skill distance. This richer distributional specification is meant to capture the idea that workers are able to tell roughly how different a job is from their current one (absolute skill distance), but not necessarily whether it's higher- or lower-skill (relative distance). In this version, workers choose a search strategy that determines the distribution of **absolute** skill distance from which they are drawing their new job as follows:

$$D(s) \sim N(\mu_D 2^{s-1}, \sigma_D^2 \exp(1.1s)) \tag{8}$$

where μ_D and σ_D are distributional scaling parameters to be estimated. Intuitively, choosing a higher s means a larger mean absolute skill distance as well as higher variance in the distribution. The skill level of the new job is assumed to be centered around the worker's current job skill level (as suggested by the symmetry of relative skill distance around the worker's source job as shown in Figure 1).

Whether **realized** relative skill distance $d_{ij'}$ is positive or negative (upward or downward move) then depends on a direction parameter p_{up} (reflecting the idea that workers don't observe new job skill level $\kappa_{j'}$ or quality $q_{j'}$ ex-ante) and a targeting parameter τ. To provide some intuition for what these distributions look like in practice, Figure 5 shows the distribution of new job skill levels $k_{j'}$ for each non-zero search strategy (recall that for $s = 0$, workers simply remain in the same occupation, and thus get the same skill level). This example shows distributions for a worker with current job skill level $\kappa_j = 0.5$ (hence the distributions are centered around 0.5). This specification reflects the idea that workers may target their job search in approximate ranges of absolute skill distance ("I want a job similar to what I'm doing now" vs. "I want to do something totally different").

Due to the CRRA utility specification and discontinuities in the skill level distributions, this version of the model does not permit a closed-form solution for the worker's optimal search strategy. Therefore, I use simulated method of moments to estimate the model parameters. I estimate eight parameters in total: the parameters of the wage equation (capturing the wage effects of skill mismatch (β_2), the interactions of education level*skill mismatch

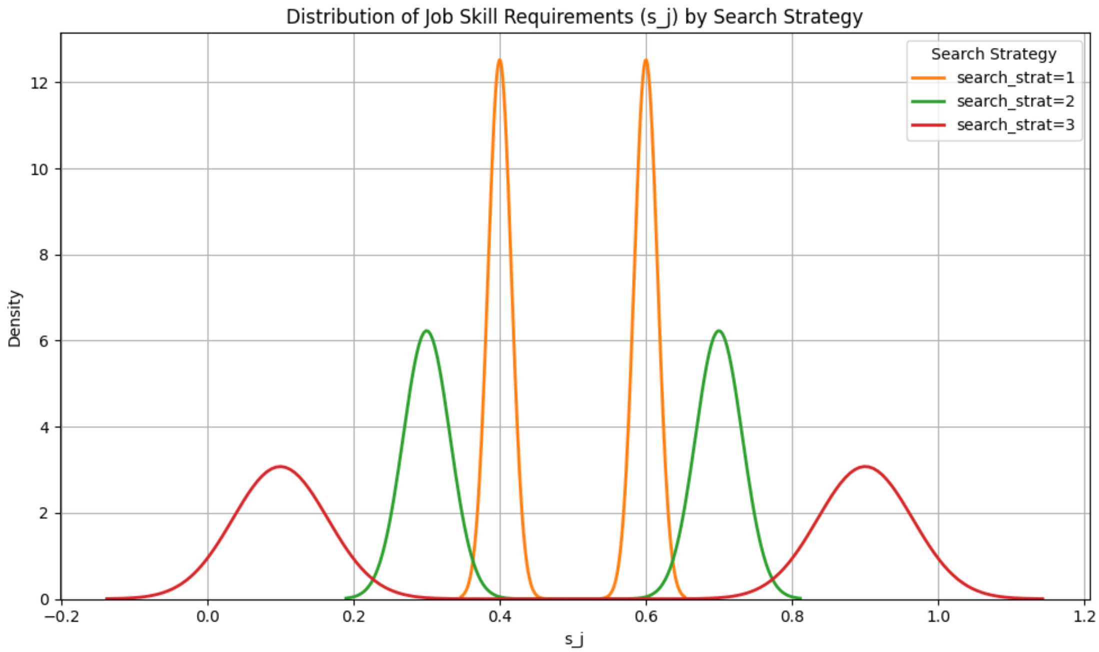


Figure 5: Distribution of new job skill by search strategy

(β_3), and education level*job quality (β_4); β_1 is held fixed at 1 for scaling), the scaling parameters of the new job skill distribution δ_μ and δ_σ, and the directional parameters of the new job skill distribution (τ, which captures the extent to which workers are able to target higher-skill jobs, and the probability of moving up vs. down the skill ladder *by education category*: $p_{up,non-col}$ and $p_{up,col}$). Note that the probability of making an upward move is permitted to vary with education level, reflecting patterns observed in the data.

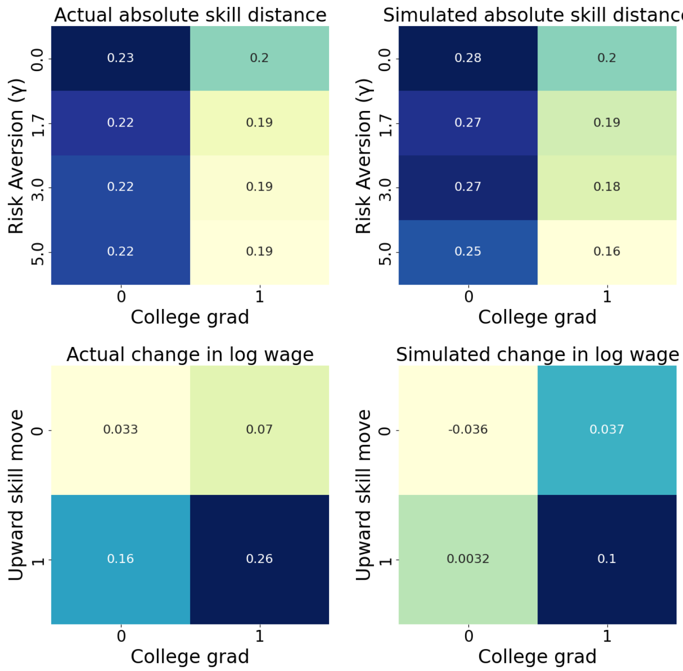
I estimated the model by matching moments relating to the absolute skill distance and wage outcomes of each respondent's largest (in terms of absolute skill distance) transition in the sample. In particular, the estimation targets the mean and standard deviation of absolute skill distance for each education-by-risk tolerance group, as well as the mean and standard deviation of wage growth for each of these groups. As there are two education levels and four levels of risk tolerance, this results in 32 targeted moments.

4.3 Parameter estimates and fit

The model is able to replicate empirical patterns of interest and closely matches data moments. In particular, as shown in Figure 6, we see that the model generates a negative relationship between absolute skill distance of transitions and risk aversion, as observed in the data. Additionally, realized wage growth is higher for moves up the skill ladder, and higher for college-educated compared to non-college-educated workers.

The parameter estimates also align with the empirical patterns documented previously.

Figure 6: Moment match



In particular, as shown in Table 11, the effect of skill distance on wages (β_2 and β_3) is small compared to the impact of job quality and education level (β_1 and β_4) (recall that β_1 is fixed at 1 for scaling). Additionally, college-educated workers ($p_{up,col}$) are much more likely to move up the skill ladder than non-college-educated workers ($p_{up,non-col}$), which is consistent with the empirical result that a college degree predicts relative skill distance. Notably, this was not a targeted moment. Finally, the positive estimate for ($\tau > 0$) indicates that workers are able to noisily target higher-skill jobs to some extent.

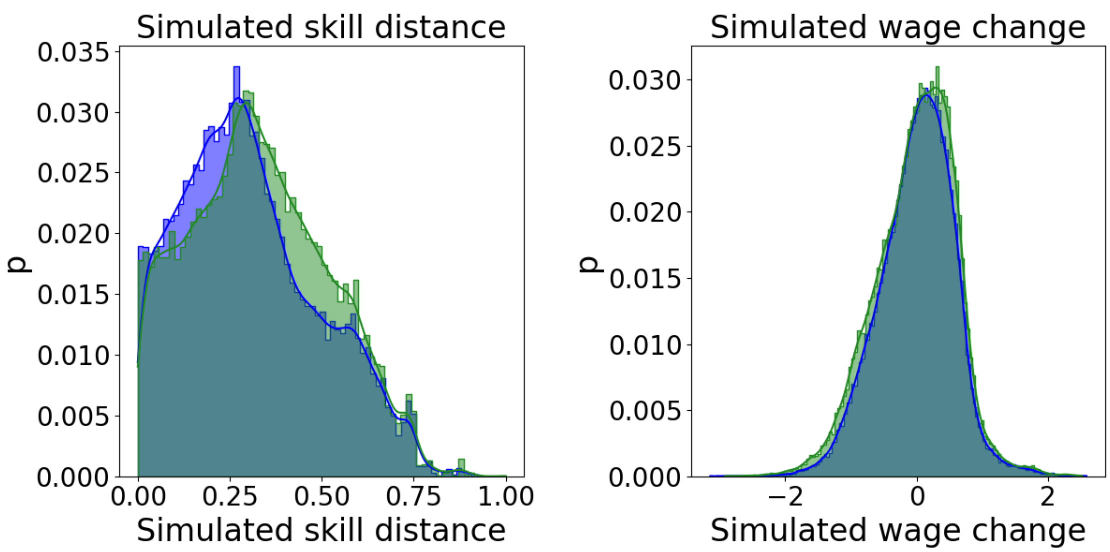
Table 11: Parameter estimates

Parameter	Value
β_1	1.0000
β_2	-0.0331
β_3	-0.0233
β_4	1.3091
δ_μ	0.0083
δ_σ	0.0162
τ	0.1616
$p_{\text{up, non-col}}$	0.2272
$p_{\text{up, col}}$	0.6786

4.4 Counterfactual: Reducing Riskiness of Job Search

We can use the model to explore the impact of risk on worker's transition decisions. In particular, to the extent that larger transitions are riskier due to higher variance in outcomes, risk-averse workers may be sacrificing potential wage gains from larger transitions. To explore this idea, I run a counterfactual simulation with much lower variance (dividing the estimated scaling parameter δ_σ by 10). Results are shown in Figure 7. Distributions of skill distance and wage change using the actual estimated parameters are shown in blue, while distributions generated using the lower δ_σ value are shown in green. As anticipated, reducing the variance component of risk (δ_σ) increases skill distance. However, the effect on wages is mixed—the distribution of wage changes becomes more skewed relative to the baseline, with a higher median but lower average. Notably, the probability of moving up or down the skill ladder was unchanged. Simply reducing the variance in outcomes of larger transitions, while preserving the downside risk, induces workers to make larger transitions.

Figure 7: Counterfactual simulation: reducing risk



4.5 Counterfactual: Skills Training vs. Job Search Assistance

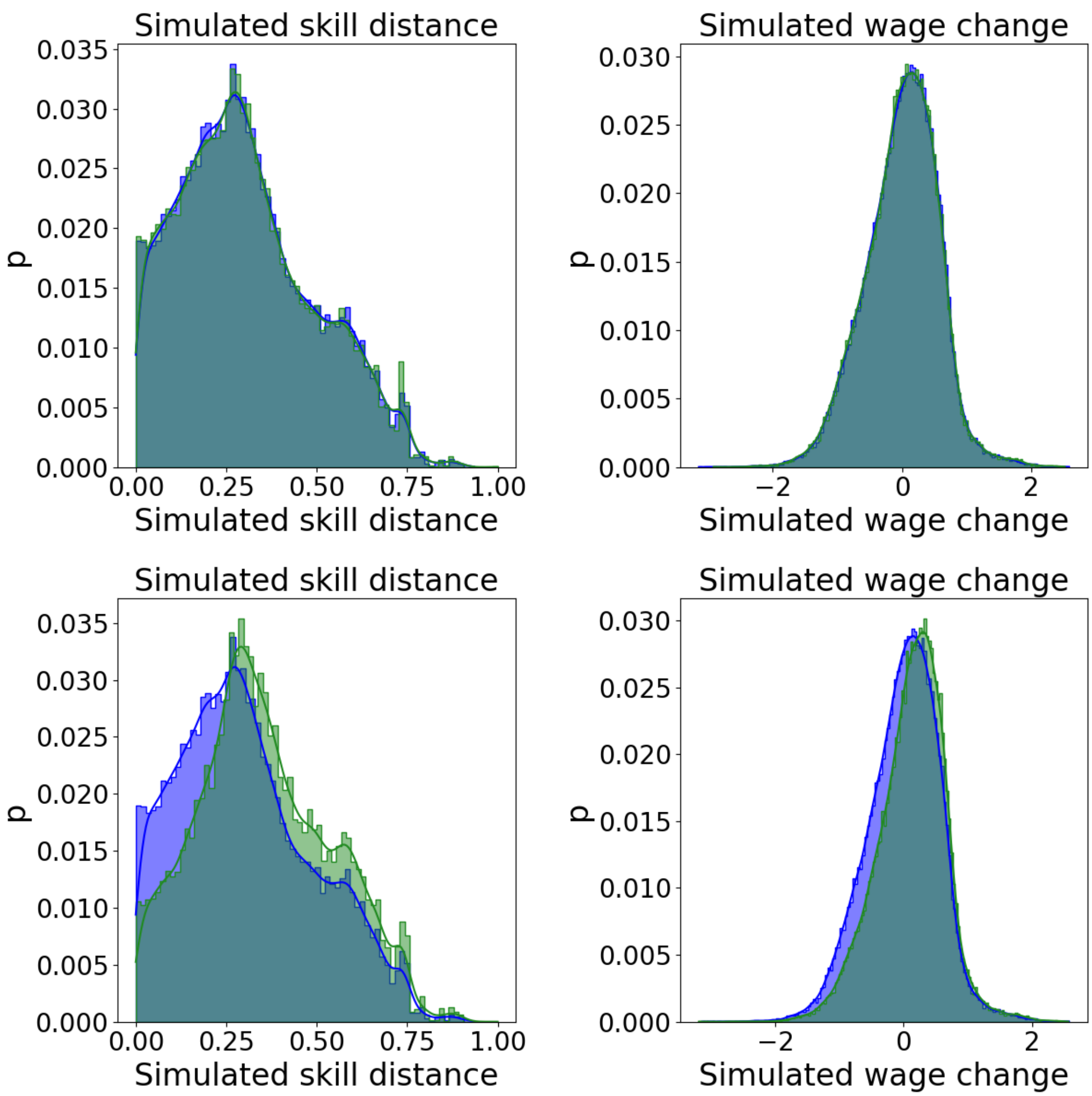
The relative importance of skill mismatch compared to risk aversion in worker transition decisions has important implications for the effectiveness of different active labor market policies. I use the model to present a stylized example of this dynamic. In particular, to the extent that workers are avoiding larger transitions due more to risk aversion than a lack of the necessary skills, job search assistance that tempers the riskiness of larger moves will be more effective at improving wage outcomes than skill training programs.

I first simulate the effects of a "skills training" intervention that increases each worker's current skill level s_i by a moderate amount (based on the skill updating rate over a one-year period). As shown in the top column of Figure 8, this intervention does not shift worker search strategies or wage growth outcomes. This is due to the fact that the estimated skill mismatch penalty ($\beta_2 + \beta_3$) is small compared to the effect of job quality, and most workers are already relatively highly skilled compared to the distribution of jobs they are drawing from. Note that this is likely an overly restrictive characterization of most skills training interventions, as it assumes that the intervention does not change the distribution of jobs the worker is drawing from (whereas many skills training interventions could feasibly be signaled to employers, thus presumably enhancing workers' access to higher-skill jobs).

I next simulate the effect of a "job search assistance" intervention that increases the targeting parameter τ by $\approx 1/3$ of the std. deviation of absolute skill distance. In other words, this intervention helps workers to better target higher-skill jobs, shifting the distributions they are drawing from to the right. As expected, many workers choose to make larger transitions when facing more favorable distributions. This can be seen in the bottom lefthand graph in Figure 8, as the distribution of realized absolute skill distances of transitions shifts rightward, with a particular redistribution of mass from the lower values of absolute skill distance. This combination of larger transitions and better job targeting results in higher wage growth for workers on average, as it allows them to move into higher-skill jobs.

While these simplified counterfactuals abstract from much of the real-world complexity of these policies, they capture an important idea. To the extent that workers are not making large transitions because of risk aversion rather than insufficient skills, skills training will be less effective than we would expect without accounting for risk aversion. For example, much of the discourse around displaced manufacturing workers impacted by the "China shock" has been focused on retraining and skills updating. However, such policies may fail to induce labor reallocation if risk aversion is also at play.

Figure 8: Counterfactual simulations: skill training vs. job search assistance



5 Conclusion

The results presented above show that large, steep transitions up the job ladder yield large and immediate wage growth premiums compared to other transitions. That is, workers moving into jobs for which they are meaningfully underskilled realize the highest wage growth upon transition, even compared to workers whose skills are well-matched to their new job. However, such transitions are rare, which is often attributed to skill mismatch costs. This paper presents risk as an additional explanation. In particular, to the extent that larger occupational transitions are riskier and workers are risk averse, this risk may discourage big career jumps. Empirical patterns support this hypothesis, and a simple model of worker transition decisions incorporating this idea is able to match observed transition outcomes quite well. Directions for future research include exploring the role of selection in making larger upward moves, which is partially addressed in this analysis with worker fixed effects, but is difficult to fully account for without firm-side data. The role of worker risk tolerance compared to skill mismatch in transition decisions has potentially important implications for active labor market policies, such as weighing the benefits of job search assistance compared to retraining.

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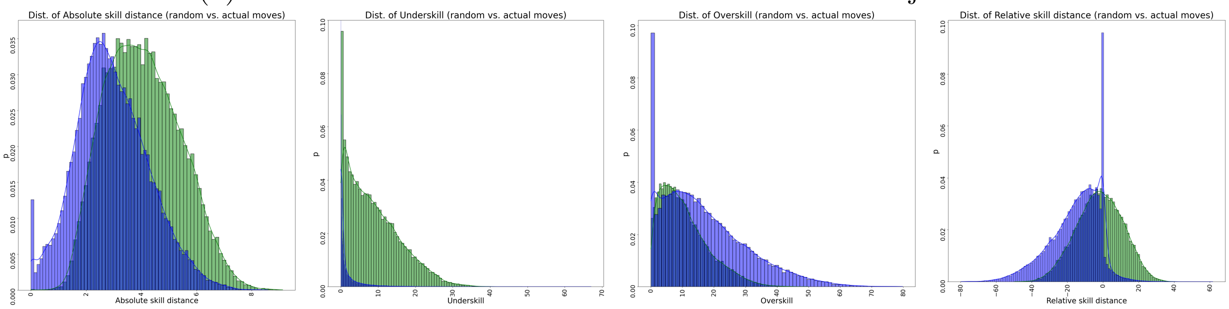
A Skill distance measures

A.1 Distributions of skill distance with random job transitions

The distributions of skill distances with moves to randomly drawn occupations are shown in green, while the actual distributions (based on actual observed job transitions in the data) are shown in blue.

Figure 9: Skill distances of job transitions (random vs. actual moves)

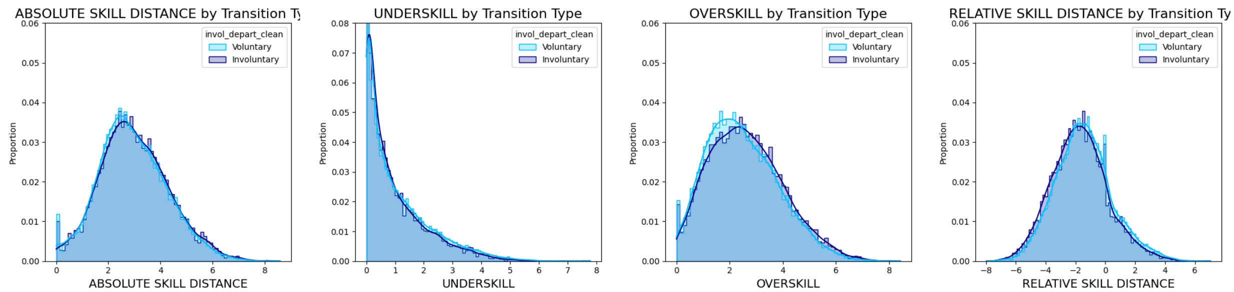
(a) Distances between worker skills and destination job skills



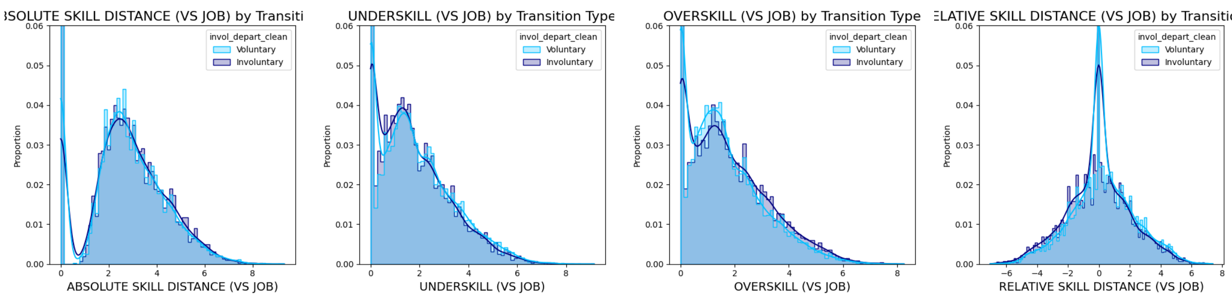
A.2 Distributions of skill distance by transition type (voluntary vs. involuntary)

Figure 10: Skill distances of job transitions

(a) Distances between worker skills and destination job skills



(b) Distances between source and destination job skills



B Main results including NLSY79 cohort

[PLACEHOLDER - TO BE UPDATED]

C Main results with various control sets

The main results presented above are generally robust to the set of control variables used.

C.1 Training

Table 12: Any employer-provided training in first year of new job

	(1)	(2)	(3)	(4)
Absolute skill distance	0.003***	0.004***	0.004***	0.003*
	(0.001)	(0.001)	(0.001)	(0.001)
Controls:				
Demographics	✓	✓	✓	
Job & transition vars.		✓	✓	✓
Year & industry/occ cat. FEs			✓	✓
Individual FEs				✓
R2	0.013	0.018	0.042	0.267
N	33508.000	32707.000	32707.000	31616.000

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

Table 13: Any employer-provided training in first year of new job

	(1)	(2)	(3)	(4)
Underskill	0.012***	0.011***	0.009***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)
Overskill	-0.000	0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.002)
Controls:				
Demographics	✓	✓	✓	
Job & transition vars.		✓	✓	✓
Year & industry/occ cat. FEs			✓	✓
Individual FEs				✓
R2	0.016	0.020	0.043	0.267
N	33508.000	32707.000	32707.000	31616.000

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

Table 14: Any employer-provided training in first year of new job

	(1)	(2)	(3)	(4)
Relative skill distance	0.009***	0.008***	0.007***	0.006***
	(0.001)	(0.001)	(0.001)	(0.002)
Controls:				
Demographics	✓	✓	✓	
Job & transition vars.		✓	✓	✓
Year & industry/occ cat. FEs			✓	✓
Individual FEs				✓
R2	0.015	0.019	0.042	0.267
N	33508.000	32707.000	32707.000	31616.000

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

C.2 Wage level vs. occupation mean

Table 15: Wage level in first year of new job vs. occupation mean

	(1)	(2)	(3)	(4)
Absolute skill distance	-0.041***	-0.026***	-0.025***	-0.028***
	(0.002)	(0.002)	(0.002)	(0.002)
Controls:				
Demographics	✓	✓	✓	
Job & transition vars.		✓	✓	✓
Year & industry/occ cat. FEs			✓	✓
Individual FEs				✓
R2	0.290	0.455	0.554	0.687
N	32685.000	32031.000	32031.000	30933.000

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

Table 16: Wage level in first year of new job vs. occupation mean

	(1)	(2)	(3)	(4)
Underskill	0.024***	0.031***	0.000	-0.004*
	(0.002)	(0.002)	(0.002)	(0.002)
Overskill	-0.057***	-0.042***	-0.031***	-0.033***
	(0.002)	(0.002)	(0.002)	(0.003)
Controls:				
Demographics	✓	✓	✓	
Job & transition vars.		✓	✓	✓
Year & industry/occ cat. FEs			✓	✓
Individual FEs				✓
R2	0.300	0.465	0.555	0.687
N	32685.000	32031.000	32031.000	30933.000

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

Table 17: Wage level in first year of new job vs. occupation mean

	(1)	(2)	(3)	(4)
Relative skill distance	0.064***	0.056***	0.026***	0.020***
	(0.002)	(0.002)	(0.002)	(0.003)
Controls:				
Demographics	✓	✓	✓	
Job & transition vars.		✓	✓	✓
Year & industry/occ cat. FEs			✓	✓
Individual FEs				✓
R2	0.299	0.465	0.554	0.686
N	32685.000	32031.000	32031.000	30933.000

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

C.3 Wage growth from job transitions

Table 18: Wage Growth from job transitions

	(1)	(2)	(3)	(4)
Absolute skill distance	-0.013***	-0.026***	-0.025***	-0.028***
	(0.002)	(0.002)	(0.002)	(0.002)
Controls:				
Demographics	✓	✓	✓	
Job & transition vars.		✓	✓	✓
Year & industry/occ cat. FEs			✓	✓
Individual FEs				✓
R2	0.007	0.255	0.391	0.582
N	32031.000	32031.000	32031.000	30933.000

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

Table 19: Wage Growth from job transitions

	(1)	(2)	(3)	(4)
Underskill	0.043***	0.031***	0.000	-0.004*
	(0.002)	(0.002)	(0.002)	(0.002)
Overskill	-0.032***	-0.042***	-0.031***	-0.033***
	(0.002)	(0.002)	(0.002)	(0.003)
Controls:				
Demographics	✓	✓	✓	
Job & transition vars.		✓	✓	✓
Year & industry/occ cat. FEs			✓	✓
Individual FEs				✓
R2	0.024	0.269	0.392	0.583
N	32031.000	32031.000	32031.000	30933.000

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

Table 20: Wage Growth from job transitions

	(1)	(2)	(3)	(4)
Relative skill distance	0.057***	0.056***	0.026***	0.020***
	(0.002)	(0.002)	(0.002)	(0.003)
Controls:				
Demographics	✓	✓	✓	
Job & transition vars.		✓	✓	✓
Year & industry/occ cat. FEs			✓	✓
Individual FEs				✓
R2	0.023	0.269	0.390	0.581
N	32031.000	32031.000	32031.000	30933.000

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

C.4 Relationship between risk aversion and skill distances

Table 21: Absolute J2J skill distance and risk tolerance

	(1)	(2a)	(2b)	(3)	(4)
Risk tolerance (general)	0.004**	0.005**	0.005**	0.005**	0.005***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Controls:					
Demographics	✓	✓	✓	✓	✓
Job & transition vars.		✓	✓	✓	✓
Year & industry/occ cat. FEs				✓	✓
R2	0.0291	0.0349	0.0352	0.0643	0.1249
N	31214.0	30488.0	30488.0	30488.0	30461.0

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

Table 22: J2J Underskill distance and risk tolerance

	(1)	(2a)	(2b)	(3)	(4)
Risk tolerance (general)	-0.003	-0.002	-0.002	-0.003	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Controls:					
Demographics	✓	✓	✓	✓	✓
Job & transition vars.		✓	✓	✓	✓
Year & industry/occ cat. FEs				✓	✓
R2	0.0327	0.0395	0.0405	0.0559	0.0831
N	31214.0	30488.0	30488.0	30488.0	30461.0

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

Table 23: J2J Overskill distance and risk tolerance

	(1)	(2a)	(2b)	(3)	(4)
Risk tolerance (general)	0.006***	0.006***	0.006***	0.007***	0.007***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Controls:					
Demographics	✓	✓	✓	✓	✓
Job & transition vars.		✓	✓	✓	✓
Year & industry/occ cat. FEs				✓	✓
R2	0.0440	0.0488	0.0490	0.0870	0.1605
N	31214.0	30488.0	30488.0	30488.0	30461.0

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

Table 24: Relative J2J skill distance and risk tolerance

	(1)	(2a)	(2b)	(3)	(4)
Risk tolerance (general)	-0.006***	-0.006***	-0.006***	-0.006***	-0.006***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Controls:					
Demographics	✓	✓	✓	✓	✓
Job & transition vars.		✓	✓	✓	✓
Year & industry/occ cat. FEs				✓	✓
R2	0.0501	0.0552	0.0558	0.0856	0.1407
N	31214.0	30488.0	30488.0	30488.0	30461.0

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

D Main results using skill distance vs. source job

The results presented in the main analysis above are directionally similar when using the skill distance between jobs ('J2J') instead of the distance between the destination job skills and the worker's current skill bundle based on their full labor market history.

D.1 Training

Table 25: Any employer-provided training in first year of new job

	(1)	(2)	(3)	(4)
J2J Abs. distance	0.005***	0.006***	0.005***	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)
Controls:				
Demographics	✓	✓	✓	
Job & transition vars.		✓	✓	✓
Year & industry/occ cat. FEs			✓	✓
Individual FEs				✓
R2	0.013	0.018	0.042	0.269
N	33320.000	32550.000	32550.000	31461.000

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

Table 26: Any employer-provided training in first year of new job

	(1)	(2)	(3)	(4)
J2J Underskill	0.011***	0.010***	0.009***	0.008***
	(0.001)	(0.001)	(0.002)	(0.002)
J2J Overskill	-0.002*	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Controls:				
Demographics	✓	✓	✓	
Job & transition vars.		✓	✓	✓
Year & industry/occ cat. FEs			✓	✓
Individual FEs				✓
R2	0.015	0.020	0.043	0.268
N	33508.000	32707.000	32707.000	31616.000

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

Table 27: Any employer-provided training in first year of new job

	(1)	(2)	(3)	(4)
J2J Relative distance	0.009***	0.008***	0.008***	0.006***
	(0.001)	(0.001)	(0.002)	(0.002)
Controls:				
Demographics	✓	✓	✓	
Job & transition vars.		✓	✓	✓
Year & industry/occ cat. FEs			✓	✓
Individual FEs				✓
R2	0.015	0.019	0.042	0.267
N	33508.000	32707.000	32707.000	31616.000

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

D.2 Wage level vs. occupation mean

Table 28: Wage level in first year of new job vs. occupation mean

	(1)	(2)	(3)	(4)
J2J Abs. distance	-0.022***	-0.009***	-0.023***	-0.018***
	(0.002)	(0.002)	(0.002)	(0.002)
Controls:				
Demographics	✓	✓	✓	
Job & transition vars.		✓	✓	✓
Year & industry/occ cat. FEs			✓	✓
Individual FEs				✓
R2	0.285	0.453	0.554	0.686
N	32506.000	31878.000	31878.000	30786.000

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

Table 29: Wage level in first year of new job vs. occupation mean

	(1)	(2)	(3)	(4)
J2J Underskill	0.014***	0.032***	0.008***	0.003
	(0.002)	(0.002)	(0.002)	(0.002)
J2J Overskill	-0.045***	-0.045***	-0.039***	-0.029***
	(0.002)	(0.002)	(0.002)	(0.002)
Controls:				
Demographics	✓	✓	✓	
Job & transition vars.		✓	✓	✓
Year & industry/occ cat. FEs			✓	✓
Individual FEs				✓
R2	0.292	0.464	0.556	0.687
N	32685.000	32031.000	32031.000	30933.000

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

Table 30: Wage level in first year of new job vs. occupation mean

	(1)	(2)	(3)	(4)
J2J Relative distance	0.040***	0.052***	0.031***	0.021***
	(0.002)	(0.002)	(0.002)	(0.002)
Controls:				
Demographics	✓	✓	✓	
Job & transition vars.		✓	✓	✓
Year & industry/occ cat. FEs			✓	✓
Individual FEs				✓
R2	0.290	0.464	0.554	0.686
N	32685.000	32031.000	32031.000	30933.000

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

D.3 Wage growth from job transitions

Table 31: Wage Growth from job transitions

	(1)	(2)	(3)	(4)
J2J Abs. distance	0.001	-0.009***	-0.023***	-0.018***
	(0.002)	(0.002)	(0.002)	(0.002)
Controls:				
Demographics	✓	✓	✓	
Job & transition vars.		✓	✓	✓
Year & industry/occ cat. FEs			✓	✓
Individual FEs				✓
R2	0.006	0.251	0.390	0.581
N	31878.000	31878.000	31878.000	30786.000

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

Table 32: Wage Growth from job transitions

	(1)	(2)	(3)	(4)
J2J Underskill	0.052***	0.032***	0.008***	0.003
	(0.002)	(0.002)	(0.002)	(0.002)
J2J Overskill	-0.052***	-0.045***	-0.039***	-0.029***
	(0.002)	(0.002)	(0.002)	(0.002)
Controls:				
Demographics	✓	✓	✓	
Job & transition vars.		✓	✓	✓
Year & industry/occ cat. FEs			✓	✓
Individual FEs				✓
R2	0.034	0.268	0.394	0.583
N	32031.000	32031.000	32031.000	30933.000

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

Table 33: Wage Growth from job transitions

	(1)	(2)	(3)	(4)
J2J Relative distance	0.071***	0.052***	0.031***	0.021***
	(0.002)	(0.002)	(0.002)	(0.002)
Controls:				
Demographics	✓	✓	✓	
Job & transition vars.		✓	✓	✓
Year & industry/occ cat. FEs			✓	✓
Individual FEs				✓
R2	0.034	0.267	0.391	0.581
N	32031.000	32031.000	32031.000	30933.000

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

D.4 Relationship between risk aversion and job-to-job ('J2J') skill distances

Table 34: Absolute J2J skill distance and risk tolerance

	(1)	(2a)	(2b)	(3)	(4)
Risk tolerance (general)	0.006***	0.006***	0.006***	0.006***	0.007***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Controls:					
Demographics	✓	✓	✓	✓	✓
Job & transition vars.		✓	✓	✓	✓
Year & industry/occ cat. FEs				✓	✓
R2	0.0170	0.0233	0.0237	0.0629	0.1640
N	31044.0	30347.0	30347.0	30347.0	30322.0

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

Table 35: J2J Underskill distance and risk tolerance

	(1)	(2a)	(2b)	(3)	(4)
Risk tolerance (general)	0.002	0.002	0.002	0.003	0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Controls:					
Demographics	✓	✓	✓	✓	✓
Job & transition vars.		✓	✓	✓	✓
Year & industry/occ cat. FEs				✓	✓
R2	0.0120	0.0261	0.0271	0.0938	0.2001
N	31214.0	30488.0	30488.0	30488.0	30461.0

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

Table 36: J2J Overskill distance and risk tolerance

	(1)	(2a)	(2b)	(3)	(4)
Risk tolerance (general)	0.004*	0.004	0.004*	0.004*	0.004**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Controls:					
Demographics	✓	✓	✓	✓	✓
Job & transition vars.		✓	✓	✓	✓
Year & industry/occ cat. FEs				✓	✓
R2	0.0081	0.0125	0.0128	0.1393	0.3460
N	31214.0	30488.0	30488.0	30488.0	30461.0

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

Table 37: Relative J2J skill distance and risk tolerance

	(1)	(2a)	(2b)	(3)	(4)
Risk tolerance (general)	-0.002	-0.001	-0.001	-0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Controls:					
Demographics	✓	✓	✓	✓	✓
Job & transition vars.		✓	✓	✓	✓
Year & industry/occ cat. FEs				✓	✓
R2	0.0014	0.0148	0.0157	0.1621	0.3899
N	31214.0	30488.0	30488.0	30488.0	30461.0

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