Risk Aversion, Occupation Choice, and Earnings Dynamics*

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Abstract

Risk aversion is a fundamental element in labor market decisions, which inherently involve risks. This paper examines how risk aversion influences occupational choices and earnings inequality, using data from the NLSY97. Descriptive findings indicate that more risk-averse workers tend to have lower earnings, with the earnings gap widening as their careers advance. Moreover, the evidence shows that risk-averse individuals are more likely to choose occupations with higher earnings stability but limited opportunities for earnings growth. To identify the causal effect of risk aversion on earnings and its underlying mechanisms, I develop a structural model of occupational choice that incorporates human capital accumulation and heterogeneity in risk aversion. The model is estimated using the EM algorithm with the Conditional Choice Probability estimator to accommodate unobserved heterogeneity. The estimated model confirms the considerable difference in the distribution of shocks to productivity across occupations, indicating the incentive for risk-averse workers to choose higher stability than the others. The decomposition of the earnings gap between risk attitude groups suggests that around 95 percent of the gap is due to risk aversion in occupation choices. Moreover, differences in human capital accumulation across occupations explain more than half of the gap, emphasizing the role of dynamic components of risk aversion effects. Using the estimated model, I show that risk-averse workers choose more profitable occupations under social insurance program with earnings floor, and thus earnings are redistributed from risk-tolerant workers to risk averse-ones.

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1 Introduction

Economic decisions are often made under uncertainty, and this is particularly true in the context of labor markets.[1] The risks inherent in labor market decisions are neither diversifiable nor insurable through financial markets, rendering risk aversion a crucial factor in the decision-making process. Consequently, the substantial heterogeneity in risk aversion, as documented in the existing literature, can lead to considerable disparities in labor market decisions and subsequent earnings.[2] While personality traits like risk aversion may significantly influence the distribution of labor market outcomes, the existing literature on earnings inequality has largely overlooked these non-productive attributes, instead focusing predominantly on productive factors such as cognitive skills. [3] However, risk aversion can influence workers' productivity through its effect on their investment decisions. Additionally, self-selection based on worker characteristics has been recognized as a crucial determinant of labor market outcomes, potentially comparable to the influence of differences in productivity. (Roy, 1951). Despite the theoretical significance of risk aversion in labor market decisions, empirical research directly examining the relationship between risk aversion and labor market outcomes remains limited.

Quantifying the effect of risk aversion on labor market outcomes is also closely tied to assessing the welfare impacts of social insurance policies. In the absence of full insurance, risk-averse workers must account for economic risks when making labor market decisions, which may prevent them from sorting into careers aligned with their comparative advantages, leading to inefficient labor market allocations. Social insurance programs such as Guaranteed Basic Income (GBI)

[1] Cunha and Heckman (2016) and Lindenlaub (2017) present that significant portion of the variation in labor market outcomes stems from uncertainty from workers' perspectives.

[2] Dohmen and Falk (2011) provides evidence of substantial heterogeneity in self-reported risk attitudes. Patnaik et al. (2020) measure the coefficient of risk aversion for college students and show that the distribution of risk aversion is non-degenerate.

[3] Deming (2017) provides evidence on the contribution of cognitive and social skills to earnings. Heckman and Kautz (2012) summarizes the study on the predicting power of non-cognitive attributes in labor market outcomes. They argue that these personality traits, also called soft skills, can be important determinants of workers' performance in various tasks. This paper departs further from their argument in that non-cognitive features can have a strong correlation with labor market outcomes by influencing their decisions even though they are not directly related to workers' productivity.

can significantly improve workers' welfare by reducing the economic risks they face, in addition to providing tangible financial support. With a stronger insurance system in place, risk-averse workers are more likely to pursue riskier opportunities where they hold a greater comparative advantage. Although workers, on average, can benefit from better job matches, choosing riskier alternatives also implies higher expected social costs to insure minimum earnings. Given the potential trade-offs, assessing the response of risk-averse workers and their distribution is essential for understanding the welfare implications of social insurance.

In this paper, I explore the impact of diversity in risk aversion on individuals' occupational choices and the distribution of earnings, and the underlying mechanisms at play. First, I provide suggestive evidence indicating a negative correlation between the level of risk aversion and not only the levels of earnings but also the earnings trajectory over workers' lifetimes. I then present suggestive evidence that this dynamic relationship between risk aversion and earnings can be explained by the differential occupation choices made by individuals with varying degrees of risk aversion: those who are more risk-averse tend to choose careers characterized by lower but stable earnings with limited earnings growth. Next, I develop an occupation choice model with risk aversion heterogeneity, rationalizing the dynamic effect of risk aversion on earnings inequality seen in the data. Within this model, more risk-averse workers tend to self-select into occupations with lower variability of unexpected shocks and accumulate skills at different rates. Using the estimated model, I quantify the relative importance of unobserved initial heterogeneity, occupation choice, and human capital accumulation in driving the effect of risk aversion on earnings disparities. Lastly, I assess how heterogeneity in risk aversion influences the labor market consequences of the GBI program.

I first document the close relationship between risk aversion and earnings profiles. From the National Longitudinal Survey of Youth 1997 (NLSY97), I observe individual responses to hypothetical job lottery choices. This gamble choice enables the classification of individuals into four distinct risk attitude groups. Using this categorization, I show evidence of a significant premium in lifetime earnings for risk tolerance. Notably, the findings reveal that the most risk-tolerant workers have an average earnings advantage by around 10 percent relative to their most risk-averse counterparts over their lifetime, conditional on demographic variables. Moreover, this earnings premium is modest in magnitude at the beginning of one's career and subsequently expanding to as much as 20 log points with 15 years of experience. It is particularly intriguing that risk aversion correlates not only with earnings levels but also with earnings growth. This observation suggests that dynamic factors beyond instantaneous compensation for risk in labor markets contribute to differences in earnings trajectories across risk attitude groups.

I next show that occupation choice is important for explaining the dynamic relationship between risk aversion and earnings. Risk-averse workers tend to choose safer occupations in terms of earnings and those occupations result in lower returns throughout the subsequent careers. Given the focus of the paper is on risk aversion, I characterize occupations with earnings stability and profitability: workers prefer more profitable occupations but risk-averse workers also care about the stability of earnings when choosing their occupation. To measure earnings stability, I calculate the variability of earnings within each occupation using residuals from the regression of log earnings on individual-occupation fixed effects and other covariates. The profitability is measured by the logarithm of mean wages within each occupation. I regress the measured attributes of workers' occupation for each period on the risk attitude group indicators defined from the observed gamble choice to examine the effect of risk aversion on occupation choices. Additionally, to explore how choosing different occupations is associated with future earnings, I regress the log of current earnings on last-period occupational attributes conditional on current occupations.

I find that individuals with higher levels of risk aversion tend to self-select into less profitable careers with more stable earnings. In particular, the most risk-tolerant workers have on average 0.1 standard deviation (SD) lower earnings stability and 0.1 SD higher profitability. The analysis on occupation choices and earnings reveals that the one with the more profitable occupation last period tends to earn more than their counterpart: having had 1 SD higher profitability in the last period is associated with around 2 percent higher current earnings. This implies that human capital is accumulated faster in profitable careers, leading to higher earnings growth for risk-tolerant workers over time.

Motivated by the descriptive evidence on risk aversion, occupation choice, and earnings dynamics, I develop a dynamic occupation choice model that incorporates workers' heterogeneity in risk aversion, building upon Yamaguchi (2012). The purpose of the model is 1) to identify the effect of risk aversion from unobserved initial heterogeneity and 2) to understand the mechanisms underlying the risk aversion effects. First, worker characteristics such as initial skills are likely affected by risk aversion through pre-market investment decisions like education, vocational training, and internship. Second, the effect of risk aversion may consist of multiple components. For example, if workers have to pay costs for changing occupations, risk-averse workers may get tied to careers with higher stability not only because they want to avoid risks but also because they cannot afford to move to profitable occupations. Another important factor is human capital accumulation differing across occupations. Workers in more profitable occupations may accrue more valued skills, providing faster growth of human capital, which is consistent with diverging earnings gap across risk attitude groups. Therefore, the model integrates switching costs, the heterogeneity in both risk aversion and human capital, and their interaction through occupation-specific rates of human capital.

In the model, workers start their careers with differentiated risk aversion and skill endowments that are allowed to be correlated with each other. Their utility from earnings has constant relative risk aversion (CRRA) which varies with their risk aversion types. Every period, workers choose an occupation that is fully characterized by earnings stability and profitability. I allow earnings risks to be occupation-specific, where occupational attributes dictate the variance of shocks to earnings. Additionally, human capital accumulation is also occupation-specific due to differential rates of accumulation. In the model, risk aversion exerts a substantial influence on occupation choices not only directly through avoidance of risks but also indirectly via the differential accumulation of human capital across occupations and dynamic selection afterward. In addition to labor market decisions, workers are engaged in hypothetical gamble choices based on their earnings and risk aversion at a given period.

The structural model is estimated using the conditional choice probability (CCP) estimators with unobserved heterogeneity, developed by Arcidiacono and Miller (2011). This approach enables me to address three challenges that make the model intractable. First, the utility function with risk aversion introduces non-linearity of flow utility, resulting in the absence of an analytical solution for the model. Second, the model involves a large choice set and extensive state spaces, including continuous skills. The CCP estimator mitigates the need for fully solving the recursive model by leveraging the relationship between choice probability and value functions, reducing a substantial computational burden. Finally, the presence of unobserved heterogeneity in risk aversion and skill endowments makes the straightforward application of CCP estimation infeasible. To address this challenge, the expectation-maximization (EM) algorithm is employed to iteratively estimate the structural parameters while accounting for unobserved heterogeneity.

I provide the estimates from a simplified model where occupations are characterized only by the profitability and relative risk aversion coefficient is externally estimated following Kimball et al. (2008). The estimates of parameters indicate that there exists a significant difference in earnings risks across occupations: the most profitable occupation has around 20 percent higher standard deviation of transitory/persistent shocks. The estimates also confirm significant differences in the rates of human capital accumulation.

I use the estimated model to decompose the earnings gap across risk attitude groups into several components: inital heterogeneity, occupation switching costs, contemporaneous return from occupation choices, and human capital accumulation. To do so, I simulate workers' earnings and occupation profiles first without any initial heterogeneity in demographics and skills. I find that around 95% of the gap between the risk attitude group can be attributed to differential occupation choice. Next, I repeat the simulation assuming no costs in occupation changes. The remaining gap accounts for 77 percent of the gap. Then, assuming homogeneous accumulation of human capital across occupations, the gap shrinks to 23 percent of the baseline. The results highlight the importance of dynamic components in evaluating the effect of risk aversion on labor market outcomes on top of the instantaneous return to riskier occupations.

I next conduct a counterfactual analysis that evaluates the welfare implications of social insurance program which provides earnings floors interacting with the heterogeneity in risk aversion. I assess how the provision of minimum earnings facilitates workers' self-selection on skills by mitigating the variance of shocks they experience in the labor market. Moreover, I present that assuming homogeneous risk aversion can mislead the evaluation of the welfare impacts.

Related Literature

This paper contributes to the literature on the association between risk aversion and occupation choices. Previous studies document the robust correlation between risk attitudes and occupation choices regarding physical risks (DeLeire and Levy, 2004; Grazier and Sloane, 2008), self-employment (Ahn, 2010), and public sector (Buurman et al., 2012). A small body of work presents evidence of more risk-averse workers working in occupations with a lower variance of earnings (King, 1974; Bonin et al., 2007; Fouarge et al., 2014; Dillon, 2018). Although suggestive of the impact of risk aversion on career, they abstract away from the role of unobserved heterogeneity, especially skill, as a fundamental element behind career decisions. Shaw (1996) who shows the short-term correlation between risk aversion and individual income growth hints at the relation between risk aversion and human capital accumulation as a channel driving diffrential labor market outcomes. My contribution is to provide the first empirical framework that incorporates unobserved heterogeneity in studying the effect of risk aversion on occupation choices and earnings profiles.

I also add to the literature on the effect of occupation choices on earnings dynamics and distributions. The literature on career choice has provided evidence of the contribution of unobserved skills and career choices to wage disparities across different workers (Keane and Wolpin, 1997; Gould, 2002; Kambourov and Manovskii, 2009; Sullivan, 2010; Yamaguchi, 2010; Pavan, 2011; Yamaguchi, 2012; Lindenlaub, 2017; Guvenen et al., 2020; Lise and Postel-Vinay, 2020). Recent literature also shows that the heterogeneity in non-wage preference can significantly contribute to the gender wage gap through occupation choices (Wiswall and Zafar, 2018). Less investigated from the literature is the combined effect of non-wage preference and unobserved skills on labor market outcomes. In particular, preference over risks can affect the development of skills both before and after labor market entrance through decisions regarding human capital. My paper is the first to directly incorporate heterogeneity in risk aversion and the interaction with skills into the structural model of occupation choices and identify the underlying channels behind the effect of risk aversion.

Finally, my paper also contributes to the literature on risk aversion measurement. Recognizing the fundamental role of risk preference in economic decision-making, a large body of literature has made progress in developing an empirical measure of risk preferences with various instruments including self-reported risk attitudes, field experiments, and observed financial decisions (see e.g. Dohmen and Falk, 2011; Barseghyan et al., 2018). I contribute to this literature by estimating relative risk aversion using the observed occupation choices with occupation-specific risks.

This paper is organized as follows: Section 2 discusses the data and occupation characterization. Section 3 documents descriptive facts on the relationship between risk attitude, occupation choice, and earnings profiles. Section 4 develops a dynamic model of occupation choices with risk aversion heterogeneity. Section 5 discusses identification and estimation processes and Section 6 shows estimation results. Using the estimated model, Section 7 presents the results of the decomposing the earnings gap across risk attitude groups. Section 5 discusses potential extensions of the model. Section 9 concludes.

2 National Longitudinal Survey of Youth 1997 (NLSY97)

I use the National Longitudinal Survey of Youth 1997 (NLSY97) for the analysis. The NLSY97 is an ongoing survey that initially included 8,984 individuals born between 1980 and 1984. They provide data on basic demographics such as demographics, such as gender, race, education, and aptitude test scores. The dataset is especially well-suited for the analysis on occupation choices due to its detailed information on employment, including occupation codes, wages, and labor supply, which are available from earlier stages of individuals' careers. More importantly, the NLSY97 provides the answers to a lottery choice experiment that is related to hypothetical job offers. This helps to recover respondents' risk attitudes in the labor market. This rich dataset allows for a thorough examination of the relationship between risk preferences, occupation choices, and earnings outcomes.

I focus on the 1997 cohort and thus expect less labor market detachment of females than 1979 cohort. Among 8,984 individuals, 3,084 individuals whose job lottery choices, the AFQT score, and the education information are missing are removed from the sample. Next, I drop 108 individuals who ever participated in military services. 577 individuals are dropped from the sample who never made long-term transitions into the labor market. A long-term transition means working full-time (more than 30 hours per week) for at least three consecutive years. Then, I removed all observations before the long-term transition. Observations after labor market detachment, or being unemployed for more than two consecutive years, are dropped. Lastly, those who have less than 3 observations or made a long-term transition before age 16 are dropped from the sample. The final sample includes 5,189 individuals with 55,246 yearly observations. If hourly rates of compensation are less than one dollar or larger than 100 dollars, they are considered missing since they are likely to be misreported.

2.1 Risk Attitude from Hypothetical Job Lottery Choice

I use individuals' responses to hypothetical job lottery choices to infer their risk preferences. To be specific about hypothetical lotteries, the survey asks respondents at the 14th or 15th wave, when individuals were between 26 and 30 years old:

"Suppose you are the only income earner in the family, but that your current job is ending. You have to choose between two new jobs. The first job would guarantee your current family income for life. The second job is also guaranteed for life and possibly better paying, but the income is less certain. There is a 50-50 chance that the second job will double your current family income for life and a 50-50 chance that it will cut your current family income by a third for life."

Individuals who chose the risky job are then asked:

"Suppose the chances were 50-50 that the second job would double your current family income and 50-50 that it would cut it in half Would you take the first job or the second job?"

On the contrary, those who would not take the risk in the first question are asked:

"Suppose the chances were 50-50 that the second job would double your current family income and 50-50 that it would only cut it by 20 percent. Would you take the first job or the second job?"

Depending on the responses to these hypothetical gambles, samples can be divided into four groups. The first group is most risk-tolerant in the sense that they would take the risk even if it is possible to experience an income cut more than or equal to half. The second group would take the risk if the possible loss is less than half but larger than a third. The third group is the one who would accept the risky job if the possible loss is less than a third but larger than 20 percent. Most risk-averse are the last group who never accept a risky job with more than 20 percent possible loss with half probability.

2.2 Characterization of Occupations

Occupations are defined by the 3-digit Standard Occupation Classification (SOC) code. The finest level of the SOC code is 6-digit with around 900 occupations. Although more granular level of classification is useful to capture the heterogeneity across occupations, I focus on the 3 digit level and further merge some occupations whose observations in the NLSY97 are less than 100 to the closest occupations within the same 2-digit occupation group so that I can ensure enough number of observations for the analysis. The crosswalk is available in Table A4. The final classification includes 81 occupations.

Considering the focus of this paper is on the role of risk aversion, I assume that occupations can be broadly characterized by profitability and earnings stability: with all else equal, workers would choose more profitable occupations, and risk-averse workers would prefer occupations that provide stable earnings streams within the spell.[4]

I first calculate residual earnings as a proxy for unexpected earnings shocks using the following regression in the NLSY97:

$$\ln Earnings_{ijt} = \alpha_{ij} + \lambda_t + x'_{it}\beta + \upsilon_{ijt} \tag{1}$$

where $Earnings_{ijt}$ represents the earnings of individual i with occupation j at period t. α_{ij} refers to individual-occupation fixed effects, which is to capture the unobserved match value between workers and occupations. λ_t is period fixed effects. x_{it} includes the cubic profiles of (potential) labor market experience. I define the mean of squared residual earnings within each occupation as a measure of occupation-specific earnings risks. In other words, $Risk_j = \hat{E}[\hat{\upsilon}^2_{ij't}|j' = j]$ where $\hat{E}[\cdot|j]$ represents the sample mean of observations conditional on occupation j. To construct the measure of earnings stability, I standardize the negative of $Risk_j$, denoted as $Stable_j$. Also, I derive $Earn_j = \log \hat{E}[Earnings_{ij't}|j' = j]$ the average of earnings within occupation j and define the standardized value as the profitability of the occupation ($Profit_j$).

In Table 1, I present the summary statistics on demographic and labor market outcomes of the sample. The most risk-averse group accounts for around 52% of the sample. On average, more risk-averse workers consist of more Black, women, less educated, and those with lower AFQT scores. They have lower hourly rates of earnings and work slightly less weeks per year. Finally, their occupations tend to have higher earnings stability and lower profitability.

[4]Risk-averse workers may also consider employment risks. In this paper, I focus on earnings risks since the lottery choice is explicitly about the variation of potential earnings. The descriptive evidence substantiates that risk attitudes revealed from the hypothetical gamble choice are not significantly associated with the number of weeks worked per year and the rate of transition from employment to unemployment.

3 Descriptive Evidence on Risk Preferences and Labor Market Outcomes

In this section, I present descriptive evidence of the relationship between risk aversion, earnings profiles, and occupation choices. I show that workers with higher levels of risk aversion exhibit not just lower lifetime average earnings and volatility but also slower growth of earnings. It is also presented that more risk-averse workers tend to choose occupations with higher earnings stability and lower profitability even conditional on covariates. Finally, the evidence reveals that opting for more earnings-stable less profitable occupations can lead to limited earnings growth in the future.

3.1 Risk Tolerance Premium in Earnings and Growth

I document the significant correlation between risk aversion and earnings profiles in this subsection. First, I test whether people with varied risk aversion have different levels of earnings and volatility over their lives. If less risk-averse workers pursue riskier careers with premiums in terms of earnings, they would have higher earnings and volatility. To test differences in earnings patterns across risk attitudes, I regress the lifetime average and variability of individual earnings on risk attitude group indicators. Especially, I estimate

$$y_i = \alpha + \sum_{g=1}^{3} \beta_g \mathbf{1}(G_i = g) + X_i'\beta + \epsilon_i \tag{2}$$

where y_i is the dependent variable (lifetime average and standard deviation of earnings), G_i represents the risk attitude group variable taking values from 1, the most tolerant, to 4, the most averse. The omitted group is the most risk-averse group. The parameter of interest is β_g which measures the average difference in the dependent variable relative to the most averse group. X_i is a vector of observed worker characteristics. I control for various worker characteristics as risk attitude elicited from job lottery choices is correlated with observed worker characteristics, suggested by Table 1. They include race, gender, age-adjusted AFQT scores, and education level indicators as a baseline model. In the other specification, I additionally control for non-cognitive skill measures and parental income variables. In this case, I compare the results with and without the additional controls using the restricted sample that has all the information, to evaluate whether the change of coefficient is driven by additional control or sample restriction.

The results reveal that risk aversion has a significant negative relationship with lifetime earnings as well as volatility. Table 2 reports the coefficient estimates γ_g for each specification. The first three columns show the results on lifetime average earnings. Column (1) indicates that the most risk-tolerant workers have earnings approximately around 11 percent higher compared to the most averse workers and it gets smaller but still significantly positive as the group gets closer to the most averse group. Columns (2) and (3) show that the results are robust to controlling for additional controls: the most tolerant individuals have around 17 percent higher average earnings. Consistent with the hypothesis above, columns (4)-(6) present that earnings premium for the more risk-tolerant individuals comes with higher earnings volatility. In the baseline specification, the most tolerant individuals experience 15 log points higher standard deviation of log earnings.

I next investigate the relationship between risk aversion and earnings growth. I estimate experience-earnings profiles by risk attitude groups using the following regression model:

$$\ln Earnings_{it} = \alpha + \sum_{g=1}^{3} \beta_g \mathbf{1}(G_i = g) + \sum_{g=1}^{3} \gamma_{gt} \mathbf{1}(G_i = g) + X_i' \beta + \phi_t + \psi_{\tau(i,t)} + \epsilon_{it} \tag{3}$$

where $Earnings_{it}$ is the hourly earnings of individual i with experience t. X_i includes race, gender, AFQT scores, and education level indicators. ϕ_t and $\psi_{\tau(i,t)}$ refer to experience level and year fixed effects, respectively. The parameters of interest are γ_{gt}, the excess earnings growth of group g from experience level 1 to t relative to the most averse workers.

Figure 2 presents that the more risk-tolerant workers have steeper earnings profiles compared to the most averse. In particular, the most risk-tolerant workers experience around 20 percentage points higher growth of earnings over 14 years relative to the most averse workers. This implies that there exist dynamic components in labor market decisions contributing to the earnings gap between risk attitude groups on top of contemporaneous premiums for taking risks.

This paper posits that (part of) the observed pattern between risk aversion and earnings can be attributed to occupational segregation resulting from heterogeneous risk aversion. In Table A2, I conduct a mediation analysis to examine the extent to which occupation profiles can explain the impact of risk aversion on earnings. I first define the major occupation for each individual based on their longest-tenured occupation, while the second major occupation is defined as the one with the second longest tenure. Columns (1) and (4) estimate the same specification of the corresponding columns in Table 2 using the sample with at least two occupations. In the subsequent columns, I sequentially include fixed effects for the major and the second major occupations. The findings show that approximately 25 percent of the risk aversion effect is mediated through heterogeneity in the first major occupations, and it diminishes further conditional on the second major occupation. This indicates that not only does occupation choice matter in explaining the relationship between risk aversion and earnings but also the trajectory of one's career path could matter. In other words, the dynamic nature of occupation choices may contribute to the observed relationship between risk aversion and earnings.

3.2 Risk Aversion and Occupation Choice

I next examine how risk aversion is related to occupation choice. If different occupations exhibit different levels of earnings risk, more risk-averse workers theoretically sort into occupations with a safer earnings stream. I test the hypothesis that more risk-averse workers are more likely to be in careers with higher earnings stability. I regress occupational attributes on risk attitude group indicators:

$$y_{it} = \alpha + \sum_{g=1}^{3} \beta_g \mathbf{1}(G_i = g) + X_{it}'\beta + \psi_t + \epsilon_{it} \tag{4}$$

where y_{it} is the dependent variable (earnings stability and profitability) of the occupation that individual i holds at period t, G_i is the risk attitude group variable, X_{it} includes race, gender, age-adjusted AFQT scores, education level indicators, and experience level indicators, ψ_t is year fixed effects. β_g is the parameter of interest which indicates the excess amount of the dependent variable for group g compared to the most averse workers.

The findings in the first column of Table 3 support the idea of aversion to earnings risks, as it reveals that more risk-averse workers tend to select occupations with higher earnings stability. For example, the most tolerant workers on average choose occupations with about 0.11 standard deviation lower earnings stability. In the subsequent two columns, I estimate the same equation using the sample with the information on non-cognitive personal traits and parental income at 1997. On average, the results remain the same or become stronger. Any variation in coefficient estimates, if any, mostly comes from the change in the sample, not from controlling additional variables. Considering the negative correlation between earnings stability and profitability, risk-averse workers' choosing a higher stability may be achieved at the expense of lower profitability. The result on the profitability, presented in the rest of columns, is suggestive of this trade-off: the more averse workers hold occupations with lower profitability.

3.3 Occupational Choice and Earnings Growth

Last, I explore the implication of occupational selection based on risk aversion for earnings growth. Recent literature on human capital emphasizes the existence of specific skills acquired through on the job, transferable across occupations to varying extents, and valued differently across occupations (Lazear, 2009; Gathmann and Schönberg, 2010; Yamaguchi, 2012). This idea is particularly pertinent in this paper's context. If profitable occupations provide the opportunity to learn skills with higher returns, workers from more profitable careers can accumulate human capital, defined as the combination of skills weighted by their returns, faster than those in the other careers. In other words, risk-averse workers may experience slower growth of earnings since they are less likely to be in profitable occupations.

To provide the suggestive evidence that selecting higher profitability may lead to larger growth of earnings, I regress log earnings on last period's occupational attributes as follows:

$$\ln Earnings_{it} = \beta_p Profit_{it-1} + \beta_s Stable_{it-1} + \alpha_i + \psi_{j(i,t)} + \lambda_t + \epsilon_{it} \tag{5}$$

where $Earnings_{it}$ is hourly earnings of individual i at period t, $Profit_{it-1}$ and $Stable_{it-1}$ are profitability and stability of the occupation that i held at period $t-1$. α_i and λ_t represent individual and year fixed effects, respectively. I include $\psi_{j(i,t)}$, current occupation fixed effects. β_p and β_s estimate the return to having worked in profitable and stable jobs, conditional on current occupations. In other words, even if two workers work in the same occupation today, their earnings can differ due to their working histories. A positive β_p implies that the return to experience in profitable occupations is positive.

Table 4 indicates that the return to experience in more profitable occupations is positive and significant; having worked in occupations with an 1 standard deviation higher profitability implies around 2 percent higher earnings today. Conversely, having worked in stable occupations shows negligible return. Consequently, if a worker starts their careers in stable occupations, they are more prone to have slower growth of earnings.

In summary, the descriptive analysis suggests the existence of a significant relationship between risk aversion, earnings dynamics, and occupation choices. While suggestive, the interpretation of evidence requires additional caution as hypothetical gamble responses, collected in the middle of individual careers, may have been influenced by their wealth and labor market experiences. For example, under the assumption of decreasing relative risk aversion, those who happen to earn more at the moment of the survey become less risk-averse, which implies the reverse relationship between risk attitudes and earnings. Although previous studies suggest the attitudes elicited through the same job lottery choices remain stable against the change in earnings and employment status,[5] the conclusion about the stability of individual risk preference is still mixed in the literature. Extending the model with non-homothetic preference over earnings is suggested in

Section 8.

The analysis is also limited in studying the risk preference effect on earnings through occupation choices since multiple factors may be involved. First, as suggested by summary statistics and previous literature, risk aversion may be correlated with worker characteristics whether they are observed or not. For instance, risk-averse workers may invest less in their human capital before entering labor markets, resulting in less initial skill endowments for risk-averse workers. To the extent that correlated characteristics affect occupation choices or productivity, the risk aversion effect may absorb those effects. Second, even differential occupation choices can be relevant with various components. Different occupations have different instantaneous returns which include risk premiums. This would lead to the difference in earnings levels across workers with varied risk preferences. Moreover, as discussed above, differences in occupation choices may have a persistent influence on earnings, indicating diverging human capital accumulation. To incorporate various components related to risk aversion into one comprehensive framework, in the next section, I develop a dynamic occupation choice model with risk aversion heterogeneity and individual- and occupation-specific human capital accumulation.

4 Occupation Choice Model with Risk Preference Heterogeneity

In this section, I present a dynamic model of occupation choices. The model is built upon the task-based approach suggested by Yamaguchi (2012) in the sense that each occupation is fully characterized by a vector of task intensities and there exist multidimensional skills corresponding to each task. The main novelty of the model is the heterogeneity in risk aversion, occupation-specific distribution of shocks, and non-homothetic preference over earnings. Departing from Yamaguchi (2012), I further assume that individuals choose occupations from a discrete choice set.[6]

[5] Sahm (2012) uses the panel structure of hypothetical job lottery choices in the Health and Retirement Study (HRS) to examine whether individual risk preferences are stable over their life cycles. They find that while risk preference changes over time, the changes in income and wealth are not the driver of the change in their risk attitudes.

[6] Yamaguchi (2012) assumes that individuals choose task bundles directly. This setting is feasible because the linear utility over log earnings allows a closed-form solution to the task choice problem. In this paper, the non-linearity

At the beginning of their careers, workers are characterized by risk aversion type, γ_i, initial skill endowment, s_{i1}, and demographic variables, x_i. For expositional simplicity, the individual subscript i is suppressed hereafter throughout the section. They choose an occupation, j, from a set of occupations, $\{1, \cdots, J\}$. Each occupation of $1, \cdots, J$ can be characterized by earnings stability and profitability, $y_j = (y_{j1}, y_{j2})$. The labor market is assumed to be competitive and information on workers' employment history and skill endowments is publicly observed. Workers in occupation j also face corresponding transitory and persistent risks, all of which are formally defined in the following subsection.

The timeline of the problem is as follows: each period, a worker chooses an occupation. Earnings are realized with transitory shocks. Skills are accumulated depending on their occupations and persistent shocks. Then, the period ends.

4.1 Utility from Earnings with Risks

The assumption of a competitive labor market implies that workers are paid according to their marginal value of products. Wages are *ex-ante* stochastic with transitory shocks whose distributions vary across occupations. A worker with skill endowment $s_t \in \mathbb{R}^K$ in occupation j obtains

$$\ln w(j; s_t, e_{jt}) = \pi(y_j) + q(y_j, s_t) + e(y_j, e_{jt}) \tag{6}$$

where $e(y_j, e_{jt}) \sim N(0, \sigma^2(y_j))$ represents independent, occupation-specific transitory shocks. $e(y_j)$ can be written as $\sigma(y_j)e_{jt}$ where $\sigma(y) = a_0 + a_1' y$ and e_{jt} follows standard normal distribution. For estimation, $\pi(y_j)$ and $q(y_j, s_t)$ are parameterized as

$$\begin{aligned} \pi(y_j) &= \pi_0 + \pi_1' y_j \\ q(y_j, s_t) &= (q_0 + q_1' y_j) s_t \end{aligned} \tag{7}$$

of the utility over earnings is essential in incorporating the concept of risk aversion heterogeneity.

where π_0 and q_0 are a scalar, π_1 and q_1 are a 2 dimensional vector. Because occupational risk is a linear function of tasks, $\pi(y_j)$ absorbs the value of occupation-specific output prices and compensating differentials for occupational risks. $q(\cdot)$ represents that the return to skills can differ across occupations. Finally, earnings equation can be written as

$$\ln w(j; s_t, e_{jt}) = \pi_0 + \pi_1' y_j + q_0 s_t + (q_1' y_j) s_t + \sigma(y_j) e_{jt} \tag{8}$$

Wage parameters π_0, π_1, q_0, Q_1, and $\sigma(y_j)$ are known to workers, but the realization of shocks is unknown when they make an occupation decision.

Workers are assumed to obtain utility from earnings with constant relative risk aversion (CRRA). The relative risk aversion coefficient is determined by their risk aversion type.

$$u(w; \gamma) = \frac{w^{1-\gamma} - 1}{1 - \gamma} \tag{9}$$

4.2 Human Capital Accumulation

Every period workers accumulate skills based on their current level of skills and current occupations. Define the accumulation technology as follows

$$s_{t+1}(j; s_t, \gamma, x, \eta_{jt}) = d_0 + d_{11} s_t + d_{12} s_t^2 + d_2' y_j + d_3' x + \eta(y_j, \eta_{jt}) \tag{10}$$

where $\eta_t(y) \sim N(0, s(y))$ is a persistent shock whose standard error is parameterized as a linear function of y as $c_0 + c_1' y$. d_0 and d_1 is a scalar, representing the general accumulation and depreciation of skills. d_2 is a 2 dimensional vector implying learning by doing. In other words, skills are accumulated at a different rate depending on occupational attributes. x is a L dimensional vector of demographic information, and d_3 is a L dimensional vector which refers to learning heterogeneity across workers.

Initial skill endowments are defined as a function of demographic information.

$$s_1 = h_0 + h_1'(x', \gamma)' + \xi \tag{11}$$

where h_0 is a scalar, h_1 is a $(L+1)$ dimensional vector. $\xi \sim N(0, s_0)$ is a scalar representing unobserved individual heterogeneity.

4.3 Non-pecuniary Preference over Occupations

In addition to utility from earnings, workers obtain non-pecuniary value from working in an occupation. Non-pecuniary preference consists of two components: (dis)utility over occupational attributes and mobility costs. The former also captures costs of working in certain working environment since the attributes are defined with various features such as required skills and activities. For example, profitability is closely aligned with critical thinking and data analysis which may require special training and efforts. Non-pecuniary preference can be formulated as follows:

$$C(j; s_t, x, j_{t-1}) = (f_0 + F_1 x + f_2 s_t + F_3 y_j)' y_j - (y_{j_{t-1}} - y_j)' F_4 (y_{j_{t-1}} - y_j) \tag{12}$$

f_0 is a 2 dimensional vector representing general (dis)utility of each occupation attribute. F_1 is a $2 \times J$ matrix implying systematic differences in job preferences. This captures the possibility that workers with the same skill levels can systematically choose different occupations in reality. Ignoring demographic differences in occupation preferences might lead to biased gaps in skill endowments across worker groups. f_2 is a 2 dimensional vector, representing the (dis)utility of intensive tasks dependent on their skills: if an individual is highly skilled, they might have lower utility costs of working in highly profitable occupations. F_3 is a 2×2 diagonal matrix capturing the convexity of (dis)utility from occupational attributes. F_4 is a 2×2 diagonal matrix that represents mobility costs. Moving cost is proportional to how different the new occupation is from the last period's occupation. The difference between the two occupations is determined by the distance in their attribute vectors.

Before fully transitioning to the labor market, workers may have formed their pre-market careers such as vocational training, part-time work, or internship. This pre-market experience enables workers to get used to certain types of tasks and affects their initial occupation choices through moving costs. Therefore, I assume workers start their careers with initial task intensity as a function of demographic variables as follows.

$$y_0 = \overline{y}_0 + Y_1(x', \gamma)' \tag{13}$$

where $\overline{y}_0$ is a 2 dimensional vector and Y_1 is a $2 \times (L+1)$ matrix.

4.4 Occupation Choice Problem

At the beginning of each period, a worker chooses an occupation to maximize their lifetime value. The flow payoff includes the expected utility from earnings, non-pecuniary values, and the expected future values. The following equation represents the recursive form of the value function.

$$\begin{aligned} &V_t(\epsilon_t, s_t, \gamma, x, j_{t-1}) = \\ &\max_{j \in \{1, \cdots, J\}} \left\{ E_e\left[u(w(j; s_t, e); \gamma)\right] + C(j; s_t, x, j_{t-1}) + \epsilon_{jt} + \beta E_{\epsilon,s}[V_{t+1}(\epsilon, x, s, j) | \gamma, x, s_t, j] \right\} \end{aligned} \tag{14}$$

subject to

$$\begin{aligned} &\ln w(j; s_t, e) = \pi_0 + \pi_1' y_j + q_0 s_t + q_1 y_j s_t + e(y_j, e) \\ &s_{t+1} = d_0 + d_1 s_t + d_2' y_j + d_3'(x', \gamma)' + \eta(y_j, \eta) \\ &s_1 = h_0 + H_1(x', \gamma)' + \xi \\ &C(j; s_t, x, j_{t-1}) = (f_0 + F_1 x + f_2 s_t + F_3 y_j)' y_j - (y_{j_{t-1}} - y_j)' F_4 (y_{j_{t-1}} - y_j) \\ &y_0 = \overline{y}_0 + Y_1(x', \gamma)' \end{aligned} \tag{15}$$

where $\epsilon_t = (\epsilon_{1t}, \cdots, \epsilon_{Jt})$ refers to idiosyncratic preference shocks with Type I Extreme Value distribution.

It is noteworthy to discuss how risk aversion affects workers' lifetime utility in the model. The direct channel through which risk aversion relates to lifetime value is occupation-specific risks and occupation choices. As pointed out above, different occupations have different levels of variance of shocks $(e(y, e), \eta(y, \eta))$. Because workers choose their occupations before the realization of the shocks, risk-averse workers would prefer those with lower variance conditional on expected earnings. This selection behavior on risk aversion can also have an indirect influence on future choices due to skill accumulation. Skill is accumulated depending on occupations. In particular, if $d_{2,\text{stability}} < d_{2,\text{profitability}}$, skills are accumulated faster in the profitable careers and thus the earnings of risk-averse workers may further diverge from those of the risk-tolerant.

4.5 Lottery Choice Problem

Besides occupation choices, workers choose among hypothetical lotteries at a certain period with their earnings and risk aversion type as given. The gamble survey was asked without any tangible incentive, so they may behave differently from their actual labor market behaviors. Therefore, I assume the logarithm of the relative risk aversion coefficient in the lottery choice involves a noise with normal distribution:

$$\ln \gamma^* = \ln \gamma + \nu, \quad \nu \sim N(0, \sigma_g^2) \tag{16}$$

With their relative risk aversion given as γ^*, workers answered the gamble experiment over two rounds given their risk aversion types and earnings at the moment. They compared the safe offer, which gives the current level of earnings forever, with the offer with moderate risk, which gives twice or two-thirds of earnings with half probability. In the second round, they weighed the safe offer against another offer whose risks depended on the first round's answer. If they chose the safe one, the second risky offer would provide twice or four-fifths of earnings with half probability; if they chose the risky one, the new offer would provide twice or half of earnings with half probability.

Formally, let $g = (g_1, g_2) \in \{0,1\}^2$ be the lottery choices over two rounds with $g_r = 1$ denoting choosing the safe offer at round r. Given their current income W and the utility function on earnings $u(\cdot;\gamma^*)$, the lottery choice can be characterized by inequality conditions. For the most tolerant group whose choice is represented as $g = (0,0)$, the following inequality should hold:[7]

$$u(W;\gamma^*) \leq \frac{1}{2}\left(u\left(2W;\gamma^*\right) + u\left(\frac{1}{2}W;\gamma^*\right)\right) \tag{17}$$

Similarly, each choice can be represented by the corresponding inequalities:

$$\begin{array}{ll} \frac{1}{2}\Big(u(2W;\gamma^*) + u(\frac{1}{2}W;\gamma^*)\Big) \leq u(W;\gamma^*) \leq \frac{1}{2}\Big(u(2W;\gamma^*) + u(\frac{2}{3}W;\gamma^*)\Big) & \text{if } g = (0,1) \\ \frac{1}{2}\Big(u(2W;\gamma^*) + u(\frac{2}{3}W;\gamma^*)\Big) \leq u(W;\gamma^*) \leq \frac{1}{2}\Big(u(2W;\gamma^*) + u(\frac{4}{5}W;\gamma^*)\Big) & \text{if } g = (1,0) \\ \frac{1}{2}\Big(u(2W;\gamma^*) + u(\frac{4}{5}W;\gamma^*)\Big) \leq u(W;\gamma^*) & \text{if } g = (1,1) \end{array} \tag{18}$$

5 Estimation

To quantify the contribution of different channels to the earnings gap between risk attitude groups, I estimate the model parameters using the NLSY97. I first propose arguments about the identifiability of model parameters in the following section. Then, I describe an estimation algorithm that helps overcome several complexities residing in the dynamic programming problem with unobserved heterogeneity. I also illustrate additional restrictions on the estimation sample at the end of the section.

5.1 Identification Argument

The identification of parameters is not straightforward because of unobserved heterogeneity in risk preferences and skills. I exploit the panel structure of earnings and dynamic discrete choices as well as one-shot lottery choices to identify the model parameters.

[7] Among risky offers, riskier offers are first-order stochastically dominated by less risky offers. This implies that if a risk-averse worker prefer the riskier offer over the safe offer, they also prefer less risky offers over the safe offer.

First of all, since skills do not have natural scales and levels, I standardize the initial skill endowments so that unconditional mean and variance are 0 and 1 respectively. Then, the identification of wage and skill parameters comes from the earnings dynamics across individuals. If a certain type of individuals have higher levels of initial earnings conditional on the other characteristics, they would have higher initial skill endowments. For instance, men may have higher earnings in more routine occupations, implying more initial routine skills. If some have faster growth of earnings given employment histories, it speaks to faster growth of skills. If earnings growth is faster for those with higher AFQT scores, it hints at the faster growth of skills for high scorers. The same argument can be applied to learning by doing: conditional on employment histories up to two periods ago if a worker having worked in occupations with higher profitability last period achieves larger growth of earnings today, it implies skills are accumulated faster in such occupations. Finally, return to skills is identified from the conditional covariance of earnings between the first period and the others. Given that initial skills are normalized, the higher return to skills implies the higher covariance of initial and the other earnings. All the other parameters including risk parameters are also identified from conditional mean and covariance of earnings.

Second, risk aversion parameters and the distribution of risk aversion types are identified from hypothetical gamble choices and the discrete choice of occupations.[8] Given the observed earnings, individuals' utility over lotteries is solely determined by risk aversion parameters. Conditional on earnings, the share of lottery choice groups within observed demographic variables identifies overall risk aversion and baseline distribution of types. The variation of the shares across demographic groups can be used to identify the heterogeneous distribution of risk aversion types. Given the identification of wage and skill parameters from observed earnings profiles, the structure of occupation-specific risks is fixed conditional on state variables. Then, the share of occupation choices helps the identification of risk aversion parameters and the type distribution in the same way as lottery choices. Furthermore, the discrepancy between occupation choice and lottery choice can be utilized to identify the distribution of the noise in the lottery choice.

Third, any systematic variation of occupation choices conditional on earnings and occupation histories provides information about non-pecuniary preference over task intensities. For example, if men on average choose occupations with higher stability relative to women with all characteristics but gender identical, it speaks to the fact that they prefer earnings stability compared to their counterparts. Similarly, initial occupation choices help the identification of initial occupational inclination.

5.2 Likelihood Function

In this subsection, I provide the details of the log-likelihood function of the observed labor market profiles. For notation, define $z_{it} = (j_{it}, w_{it})$ as a pair of the occupation and the log wage of individual i at period t and $Z_i = \{z_{it}\}_t$ as the whole profile. Denote $g_i = (g_{i1}, g_{i2})$ as their lottery choices where $g_{ir} = 1$ means that i chooses the safe offer in round r. Define $\psi(s_t|s_{t-1}, x_i, \gamma_i, j_{i,t-1})$ as the probability of skill at period t, s_t, conditional on $(s_{t-1}, x_i, \gamma_i, j_{i,t-1})$ consistent with equation (10), and $\psi_1(s_1|x_i, \gamma_i)$ as the probability of initial skill s_1 conditional on (x_i, γ_i) following equation (11). Finally, a vector of model parameters, θ, consists of four components that determine the distribution of unobserved states (θ_u), risk aversion coefficients and noise (θ_r), wages (θ_w), and non-pecuniary preference (θ_p).

Risk Aversion Type Risk aversion is heterogeneous across individuals through varying γ in their utility over earnings and not observed by researchers. For simplicity, I assume two types of risk preference: high risk-averse (γ_H) and low risk-averse (γ_L). I also assume the distribution of the risk aversion type as a logit model with the latent variable as a function of demographics, i.e. $\rho(\gamma_H|x_i) = \frac{exp(\rho_0 + x_i'\rho_1)}{1+exp(\rho + x_i'\rho_1)}$.

Gamble Choice I first define the likelihood function of the hypothetical gamble choices. Under the CRRA assumption, the inequalities in (17) and (18) can be reduced into the intervals with respect to γ^*. For example, for the moderate tolerant group with $g = (0, 1)$, γ^* should be between 2 and 3.76535. The upper and the lower bound of γ^* for each inequality is summarized in Table 5.

[8] Although I parametrize the unobserved heterogeneity of risk aversion types, the non-parametric identifiability of finite mixture models with dynamic discrete choices has been proven by Kasahara and Shimotsu (2009). Especially, they show that with moderate panel periods ($T \geq 6$), the mixture model of the first-order Markov property is identified.

Therefore, the likelihood of lottery choice can be formulated with the log normal distribution of γ^*.

Optimal Policy Given the CCP estimates as $\hat{P}$, the derivation of CCP's directly follows the matrix inversion method of Hotz and Miller (1993). Define the flow payoff of individual i in occupation j as $U_j(s_{it}, \gamma_i, x_i, j_{i,t-1})$. The conditional value function of choosing occupation j can be written as

$$v_j(s_{it}, \gamma_i, x_i, j_{i,t-1}) = U_j(s_{it}, \gamma_i, x_i, j_{i,t-1}) + \beta \int \overline{V}(s', \gamma_i, x_i, j)\psi(s'|x_i, s_{it}, j)ds' \tag{19}$$

where $\overline{V}(\cdot) = E_\epsilon[V(\epsilon_t, \cdot)]$. With Type 1 Extreme Value distribution of preference shock, the conditional choice probability of occupation j becomes

$$P(j|s_{it}, \gamma_i, x_i, j_{i,t-1}) = \frac{\exp(v_j(s_{it}, \gamma_i, x_i, j_{i,t-1}))}{\sum_{j'} \exp(v_{j'}(s_{it}, \gamma_i, x_i, j_{i,t-1}))} \tag{20}$$

In other words, if one can calculate $\overline{V}(\cdot)$, they can derive the choice probability for each state.

Letting $\overline{V}$ a vector of expected values for each pair of state variables, P_j and U_j vectors of conditional choice probability and the flow payoff for occupation j, and F_j a matrix of skill transition in occupation j. Hotz and Miller (1993) propose that $\overline{V}$ can be reduced into the following form

$$\overline{V} = \left(I - \beta \sum_j (P_j \vec{\mathbf{1}}') \odot F_j \right)^{-1} \left(\sum_j P_j \odot (U_j + \epsilon_j^*) \right) \tag{21}$$

where $\vec{\mathbf{1}}$ is a vector of ones and $\odot$ represents element-wise multiplication. ϵ_j^* indicates the conditional expectation of error terms whose elements have a closed form as $C_{euler} - \ln P_j(\cdot)$.

Given $\hat{P}$ and parameters θ, the optimal policy of occupation choices can be constructed using equation (19) and (20): for all j,

$$P(j|s_{it},\gamma_i,x_i,j_{i,t-1};\hat{P},\theta)=\frac{\exp(v_j(s_{it},\gamma_i,x_i,j_{i,t-1};\hat{P},\theta))}{\sum_{j'}\exp(v_{j'}(s_{it},\gamma_i,x_i,j_{i,t-1};\hat{P},\theta))} \tag{22}$$

Labor Market Outcomes In the first period, given the unobserved skill, s_1, and the risk aversion type, γ the likelihood of observing z_{i1} can be written as

$$l_1(z_{i1}|s_1,\gamma,x_i;\hat{P},\theta)=P_1(j_{i1}|s_1,\gamma,x_i;\hat{P},\theta)\phi(w_{i1}|s_1,j_{i1};\theta) \tag{23}$$

where P_1 represents the conditional choice probability at period 1. ϕ refers to the probability density function of a normal distribution with conditional mean and variance as

$$\begin{aligned} E[w_{i1}|s_1,j_{i1}] &= \pi_0+\pi_1' y(j_{i1})+(q_0+Q_1 s_1)' y(j_{i1}) \\ V[w_{i1}|s_1,j_{i1}] &= \sigma^2(y(j_{i1})). \end{aligned} \tag{24}$$

Similarly, given (s_t,γ), the likelihood of observing z_{it} is

$$l(z_{it}|s_t,\gamma,x_i,j_{i,t-1};\hat{P},\theta)=P(j_{it}|s_t,\gamma,x_i,j_{i,t-1};\hat{P},\theta)\phi(w_{it}|s_t,j_{it};\theta). \tag{25}$$

Subsuming $(\hat{P},\theta)$, the likelihood of an individual's labor market profile conditional on γ is

$$l^*(Z_i|\gamma,x_i)=\sum_{s_1}\cdots\sum_{s_T}\psi_1(s_1|x_i)l_1(z_{i1}|s_1,\gamma,x_i)\prod_{\tau=2}^{T}\psi(s_\tau|s_{\tau-1},x_i,j_{i,t-1})l(z_{i\tau}|s_\tau,\gamma,x_i,j_{i,\tau-1}) \tag{26}$$

Finally, the individual contribution to the log-likelihood is

$$\begin{aligned} \log L(g_i,Z_i|x_i) &= \log\sum_{\gamma}\rho(\gamma|x_i)\mathcal{L}(g_i,Z_i|\gamma,x_i) \\ \mathcal{L}(g_i,Z_i|\gamma,x_i) &= l^*(Z_i|\gamma,x_i)P(g_i|\gamma,Z_i) \end{aligned} \tag{27}$$

5.3 Expectation-maximization (EM) Algorithm

Given that the model parameters can be identified, I exploit the EM algorithm to estimate the model, following the method in Arcidiacono and Miller (2011). The main goal of this approach is to overcome challenges in estimating dynamic programming problems with state-dependent unobserved heterogeneity. First, fully solving the problem is computationally costly for a couple of reasons. The utility function over earnings solves the second-order differential equation 41, which does not have a closed-form solution. This indicates that there is no analytical solution to the worker's occupation choice problem. Moreover, there are multiple state variables including last occupations and skills. Since there are many available occupations and skills are continuous, the state space becomes extensive, making the nested fixed point algorithm intractable. To circumvent the necessity of fully solving the model, Hotz and Miller (1993) propose CCP estimators that utilize the relationship between value functions and the probabilities of choosing alternatives.

Although CCP estimators can mitigate the computational costs, their direct application is infeasible because of the second challenge, unobserved heterogeneity. One requirement to implement CCP estimators is the estimated choice probabilities for all possible states, which are not available in the presence of unobserved state variables. Arcidiacono and Miller (2011) suggest the EM algorithm that iteratively updates the CCP's and estimates the parameter with the Maximum Likelihood Estimation given the updated CCP's. The key insight of their arguments holds in this article although the model departs from their setting in the sense that unobserved heterogeneity transition also depends on choices and other state variables. In the expectation step, the CCP's, the distribution of risk aversion types, initial skills, and skill transitions are updated by applying Bayes' rule to observed outcomes and previous parameter estimates. The maximization step estimates the rest of the model parameters given the estimated CCP's from the expectation stage. In the maximization stage, the log-likelihood of observed outcomes is maximized with the posterior distribution of unobserved skills as given and will be separated into multiple stages. The following subsections provide greater details of the $(m+1)$th iteration given the mth estimates of CCP's and parameters.

5.3.1 Expectation: Updating Conditional Choice Probability

Given the mth parameter and CCP estimates $(\theta^{(m)}, \hat{P}^{(m)})$ and observed outcomes (Z_i, g_i), I first update $p_{1i}^{(m)}(\gamma)$, the probability of i being risk aversion type γ, and $p_{2it}(s|\gamma)$, the probability of i having skill s at period t conditional on γ. Then, I update $\rho(\gamma|x_i)$, the probability of risk aversion types, $\psi_1(s_1|x_i)$, the probability distribution of initial skills conditional on demographics, and $\psi(s_t|s_{t-1}, x_i, j_{i,t-1})$, the transition probabilities of skill at period t given demographics and occupation at period $t-1$. Finally, the CCP's are updated with equation (22).

Update $p_{1i}(\gamma)$ and $p_{2it}(s|\gamma)$ The conditional probability of i being in a certain risk aversion type can be calculated by applying Bayes' rule. The likelihood of i's observed profile with estimates at the mth iteration is calculated with (27) as

$$L(g_i, Z_i|x_i; \theta^{(m)}, \hat{P}^{(m)}) = \sum_{\gamma} \rho(\gamma|x_i; \theta^{(m)})\mathcal{L}(g_i, Z_i|\gamma, x_i; \theta^{(m)}, \hat{P}^{(m)}) \tag{28}$$

The probability of i being γ type of risk aversion is written following Bayes' rule as

$$p_{1i}^{(m+1)}(\gamma) = \frac{\rho(\gamma|x_i)\mathcal{L}(g_i, Z_i|\gamma, x_i; \theta^{(m)}, \hat{P}^{(m)})}{L(g_i, Z_i|x_i; \theta^{(m)}, \hat{P}^{(m)})} \tag{29}$$

The probability of i having skill s at period t given the risk aversion type is also updated similarly. First, denote $l_t^*(Z_i, s_{it} = s|\gamma, x_i)$ as the likelihood of i's labor market profile with the unobserved skill at period t as s. Subsuming $\theta^{(m)}$ and $\hat{P}^{(m)}$,

$$\begin{aligned} l_t^*(Z_i, s_{it} = s|\gamma, x_i) = &\sum_{s_1} \cdots \sum_{s_{t-1}} \sum_{s_{t+1}} \cdots \sum_{s_T} \psi_1(s_1|x_i) l_1(z_{i1}|s_1, \gamma, x_i) \\ &\times \left(\prod_{\tau=2}^{t-1} \psi(s_\tau|s_{\tau-1}, x_i, j_{i,\tau-1}) l(z_{i\tau}|s_\tau, \gamma, x_i, j_{i,\tau-1}) \right) \\ &\times \psi(s|s_{t-1}, x_i, j_{i,t-1}) l(z_{it}|s, \gamma, x_i, j_{i,t-1}) \psi(s_{t+1}|s, x_i, j_{i,t}) l(z_{it}|s_{t+1}, \gamma, x_i, j_{i,t}) \end{aligned}$$

$$\times \left(\prod_{\tau=t+2}^{T} \psi(s_\tau | s_{\tau-1}, x_i, j_{i,\tau-1}) l(z_{i\tau} | s_\tau, \gamma, x_i, j_{i,\tau-1}) \right) \tag{30}$$

Then, Bayes' rule implies the conditional probability of i being in unobserved skill s at period t as

$$p_{2it}^{(m+1)}(s|\gamma) = \frac{l_t^*(Z_i, s_{it} = s|\gamma, x_i)}{l^*(Z_i|\gamma, x_i)} \tag{31}$$

Update $\rho(\gamma|x_i)$ The distribution of unobserved risk aversion types is determined by (ρ_0, ρ_1). I update $(\rho_0^{(m)}, \rho_1^{(m)})$ by maximizing the likelihood of the posterior distribution of risk aversion types, $p_{1i}^{(m+1)}$:[9]

$$(\rho_0^{(m+1)}, \rho_1^{(m+1)}) = \underset{(\rho_0, \rho_1)}{\arg\max} \sum_i \left(p_{1i}^{(m+1)}(\gamma_H) \log \rho(\gamma_H | x_i; \rho_0, \rho_1) + p_{1i}^{(m+1)}(\gamma_L) \log \rho(\gamma_L | x_i; \rho_0, \rho_1) \right) \tag{32}$$

Update $\psi_1(s_1|x_i, \gamma)$ and $\psi(s_t|s_{t-1}, x_i, j_{i,t-1})$ Equation (11) suggests that $\psi_1(s_1|x_i)$ follows the normal distribution with the conditional mean and variance determined by H_1. $H_1^{(m)}$ can be updated by maximizing the likelihood of the posterior distribution of initial skills, $p_{2i1}^{(m+1)}$:[10]

$$H_1^{(m+1)} = \underset{H_1}{\arg\max} \sum_i \sum_\gamma \int p_{2i1}^{(m+1)}(s|\gamma) \log \psi(s|x_i, \gamma) ds \tag{33}$$

The probability of skill transition is represented by (10), which could be estimated by a regression model if skills were observed. Although skills are not observed, I estimate (10) by assigning each observation the weight as the posterior distribution of (s_t, s_{t-1}). The joint probability of (s_t, s_{t-1}) given γ can be represented as the probability of s_t conditional on s_{t-1} multiplied by the probability of s_{t-1}, the latter of which is calculated as $p_{2it-1}(s_{t-1}|\gamma)$. The former is calculated

[9] This is equivalent to estimating a logit model with the relative weight given as the posterior distribution of risk aversion types.

[10] In actual estimation, the integral is replaced with the summation as skills are discretized.

as follows:

$$
\begin{aligned}
\tilde{l}_{it}^{(m+1)}(s|s_{t-1},\gamma) =& \psi^{(m)}(s|s_{t-1},x_i,j_{i,t-1})l(z_{it}|s,\gamma,x_i,j_{i,t-1}) \\
&\times \left(\sum_{s_{t+1}} \cdots \sum_{s_T} \psi^{(m)}(s_{t+1}|s,x_i,j_{i,t-1})l(z_{it+1}|s_{t+1},\gamma,x_i,j_{i,t}) \right. \\
&\left. \times \prod_{\tau=t+2}^{T} \psi^{(m)}(s_\tau|s_{\tau-1},x_i,j_{i,\tau-1})l(z_{i\tau}|s_\tau,\gamma,x_i,j_{i,\tau}) \right) \\
\tilde{p}_{2it}^{(m+1)}(s|s_{t-1},\gamma) =& \frac{\tilde{l}_{it}^{(m+1)}(s|s_{t-1},\gamma)}{\sum_{s_t} \tilde{l}_{it}^{(m+1)}(s_t|s_{t-1},\gamma)}
\end{aligned} \tag{34}
$$

Given $p_{2it-1}^{(m+1)}(s|\gamma)$ and $\tilde{p}_{2it}^{(m+1)}(s'|s,\gamma)$, equation (10) can be estimated by the following maximum likelihood estimation:[11]

$$
\begin{aligned}
&\theta_s^{(m+1)} = \\
&\arg\max_{\theta_s} \sum_i \sum_{t=2} \iint \left(\sum_\gamma p_{1i}^{(m+1)}(\gamma) p_{2it-1}^{(m+1)}(s|\gamma) \tilde{p}_{2it}^{(m+1)}(s'|s,\gamma) \right) \log \psi(s'|s,x_i,j_{i,t-1};\theta_s) ds ds'
\end{aligned} \tag{35}
$$

where θ_s represents a vector of skill transition parameters.

Update CCPs Finally, the conditional choice probability is updated following (22):

$$
\hat{P}^{(m+1)}(j|s_{it},\gamma_i,x_i,j_{i,t-1};\hat{P}^{(m)},\theta^{(m)}) = \frac{\exp(v_j(s_{it},\gamma_i,x_i,j_{i,t-1};\hat{P}^{(m)},\theta^{(m)}))}{\sum_{j'} \exp(v_{j'}(s_{it},\gamma_i,x_i,j_{i,t-1};\hat{P}^{(m)},\theta^{(m)}))} \tag{36}
$$

5.3.2 Maximization: Maximum Likelihood Estimation

Given the updated CCPs and the posterior distributions of unobserved states, the rest of the model parameters can be updated by the maximum likelihood estimation.

$$
\begin{aligned}
\max_\theta \sum_i \sum_t \sum_\gamma \sum_s \Big[& p_{1i}^{(m+1)}(\gamma) p_{2it}^{(m+1)}(s|\gamma) \\
& \log \Big(l(z_{it}|s,\gamma,x_i,j_{i,t-1};(\theta_u^{(m+1)},\theta_{-u})) P(g_i|\gamma,Z_i;(\theta_u^{(m+1)},\theta_{-u})) \Big) \Big]
\end{aligned} \tag{37}
$$

[11]In actual estimation, integrals are replaced with summations as skills are discretized.

In Appendix A, I prove that the maximization problem above is equivalent to maximizing the sum of individual log-likelihood presented by equation (27). The advantage of the suggested maximization is that the log-likelihood becomes additively separable, so the model parameters can be updated through separate stages. In particular, θ_r is estimated with the lottery choice, θ_w is estimated from the observed wage profiles, and θ_p is updated by the occupation choice given (θ_r, θ_w). Solving the dynamic programming problem is only required in the estimation of occupation choice, so the additive separability of the log-likelihood effectively reduces the number of parameters to be estimated in the dynamic programming problem. More details on the maximization step are provided in Appendix A.

5.3.3 Additional Estimation Setting

Unobserved skills are continuous variables and must be discretized to estimate the model. Although the more discrete points help better approximation of estimating the model with continuous variables, it also becomes infeasible to estimate the model as each realization of likelihood during estimation still requires calculating the value function with matrix inversion. Larger state space indicates larger matrices to be inversed, making the calculation heavier. I address the problem of the large state space by using value function approximation as suggested by Keane and Wolpin (1994). In particular, I calculate the value function with 5 discrete points for skill dimension and approximate the value function with 10 points using regression on the second-order polynomials of skills for each iteration of the likelihood function.

The estimation still calls for a couple of restrictions on the estimation sample to proceed. First, the sample is restricted to those who had positive earnings at the moment of job lottery choices. This is to ensure that job lottery choices are made based primarily on the individual's risk aversion and economic conditions, not on the components outside the model such as parental income. Second, I estimate the model with high school graduates and college graduates separately because the choice set for occupations is likely to differ across education levels. For example, professional occupations such as scientists or physicians require some qualifications that are directly connected to college degrees. Workers may determine educational attainment based on both their risk preferences and the availability of occupations in the future, but studying educational decisions is beyond the scope of this paper. Therefore, I suppose that education level is predetermined, and I distinguish the sample into two groups when estimating the model.

6 Estimation Results

In this section, I present the estimation results with several assumptions to simplify the process. First, I characterize occupations only with the profitability to reduce the number of parameters to estimate. Second, I determine individual risk aversion coefficients using the framework proposed by Kimball et al. (2008). I assume that workers' relative risk aversion with measurement error follows log normal distribution similar to the setting imposed in subsection 4.5. Using the Maximum Likelihood Estimation, I estimate the distribution of relative risk aversion. Then, I derive the conditional expected values of relative risk aversion coefficients for each risk attitude group. These coefficients are then assigned to individuals based on their risk attitude groups. The estimated values of relative risk aversion coefficients are about $0.73, 1.51, 2.8, 5.87$ for the most tolerant, the tolerant, the averse, and the most averse group, respectively.

The parameter estimates for the high school graduate and dropout sample are presented in Table 6 and Table 7. Notably, there is significant variation in the standard deviation of shocks across occupations, especially for persistent shocks. Occupations with the highest profitability exhibits around 16 percent higher standard deviation of transitory shocks and around 23 percent higher standard deviation of persistent shocks relative to the least profitable occupations. The considerable difference in occupational risks implies that workers have an incentive to select occupations based on their risk aversion.

In addition, the rate of human capital accumulation is significantly differential across occupations. The parameter estimate of occupation specific accumulation rate (d_2) is around 0.6, significant both statistically and economically. For example, workers in the occupation with the highest profitability last period can experience about 14 percent ($(q_0 + q_1 y_j)0.6 = (0.18 + 0.05 * 1)0.6$) higher earnings growth at most compared to others from the least profitable occupations. Significant difference in the rate of human capital accumulation indicates that risk-averse workers, after entering safer careers, can have a slower growth of earnings relative to those who select into profitable careers, consistent with the observation from the data in Section 3.

Furthermore, risk aversion has a significant negative relationship with initial skill. Compared to the most risk-tolerant group, the most risk-averse workers tend to have approximately 0.15 standard deviations lower skills. This difference between the extreme risk attitude groups is comparable to the effect of being in the group with higher AFQT scores, whose impact amounts to 0.16 standard deviation. It is also equivalent to the difference in earnings by about 3-3.5%.

In Figure 3, the average profiles of log earnings and profitability from the data are compared with the predicted profiles from the estimated model. The model predicts the inital earnings exactly and presents identical trends of earnings up to 4 years of experience. Although the predicted profile of earnings is slightly steeper than the observed profile between 5 years and 11 years and becomes flatter afterward, it remains closely aligned with the trend of the data. The model prediction on occupation choices shows almost the same trend with the observed choices.

7 Decomposition of Risk Aversion Effect on Earnings

The observed earnings gap across different risk attitude groups in our data may be influenced by several factors, including initial skill heterogeneity, switching costs, and human capital accumulation as well as immediate premium for risky occupations. First, as hinted in the parameter estimates, risk aversion is significantly correlated with initial skill endowments, even after the AFQT scores are controlled. The effect of differential initial skills can compound into the future earnings since skill accumulation is faster with higher skills. Second, there exist significant switching costs when changing occupations, especially farther away from the previous occupations. This means it is costly for workers to jump up to the more profitable careers if they are in low-profitability occupations. Finally, parameter estimates also present occupation-specificity of the rates of human capital accumulation.

I utilize the estimated model to disentangle the earnings gap between workers with varying degrees of risk aversion to investigate the contribution of each factor to the risk aversion effects. The decomposition process involves four steps. First, I replicate the earnings gap across risk attitude groups using the estimated model by simulating earnings and occupation choice profiles for a sample size five times larger than the actual dataset. To dissect the impact of risk aversion from that of initial heterogeneity in other characteristics, I simulate earnings and occupation choices for the same individuals, assuming no systematic heterogeneity in demographic variables initial skills, and initial job propensity. Specifically, I assume uniform demographic variables across workers, and set (H_1, Y_1) to zero. Second, I remove the friction in occupation switching by setting F_4 to be zero and simulate labor market profiles. Finally, I nullify differential human capital accumulation to isolate the effect of human capital accumulation from the premium for risky occupations. This involves setting skill transition as $s' = d_0 + d_{11}s + d_{12}s^2 + d_2\overline{y} + d_3x + \eta_j$, where $\overline{y}$ represents the average of the profitability. Using these simulated datasets, I compare the regression estimates of log lifetime average earnings on risk attitude group indicators conditional on demographics across different scenarios.

The results are presented in Table 8. In the first column, I reproduce the earnings gap across risk attitude groups using the observed sample employed in model estimation. Focusing on the two extreme groups, the most risk-tolerant workers, on average, exhibit around 11 percent higher lifetime earnings compared to the most risk-averse workers. In the baseline model, this gap is overestimated to 19 percent. The third column presents that initial heterogeneity only accounts for about 3 percent of earnings gap between two extreme groups and 97 percent can be attributed to overall impacts of risk aversion through differential occupation choices.

The effects through occupation choices can be further decomposed into several components. In the fourth column, switching costs are assumed to be zero. The remaining gap is around 77 percent of the baseline. The friction in occupation switching explains about 20 percent of the gap. In other words, risk-averse workers get stuck at their less profitable careers not just because they try to avoid risks but also they can not move up the profitable occupations due to moving costs.

The last column shows the earnings gap in the absence of differential human capital accumulation across occupations. The remaining gap, about 23 percent of the baseline, represents the instantaneous return to take riskier careers, while the difference between the last two columns implies the impact of human capital accumulation. It accounts for almost the majority of the earnings gap. In summary, the decomposition analysis reveals that most of the earnings disparities across workers with varied levels of risk aversion come from choosing different types of occupations, isolating from any initial heterogeneity whether observed or unobserved. Furthermore, the majority of the effects through occupation choices are attributed to differential accumulation rates of human capital. This implies that the effects of risk aversion on earnings may be underestimated when examined only through instantaneous compensation for risks, highlighting the role of dynamics in earnings.

8 Extension

8.1 Unemployment Risk

Unemployment risk is another important component of economic risks. Although unemployment component is omitted in the analysis because the elicited risk attitude from hypothetical job choices does not have significant correlation with the number of working weeks and employment-to-unemployment transition rate, the recent literature has documented both the significant difference in unemployment risks across occupations (e.g. Fouarge et al., 2014) and heterogeneity in preference over unemployment risks (Wiswall and Zafar, 2018).

The model can be extended to incorporate occupation-specific unemployment risks by setting the number of weeks worked stochastic and its variation to be occupation-specific. To be specific, following the selection of occupations, the duration of work (Wks_{jt}) is stochastically determined through a random distribution. This stochasticity mirrors the reality that workers may experience periods of unemployment within a year. In other words, even if individuals are observed to have occupations at the moment of interview, the possibility of job loss or failure to secure new employment remains present. Similar to wage risks, the risk of employment is specific to each occupation, where the average duration of work weeks is contingent upon occupational attributes. Moreover, the unemployment duration may also depend on individual skills. I assume that wks_{jt} adheres to a Tobit model, truncated at both lower and upper bounds, as follows.

$$
\mathrm{wks}^*_{jt} \sim N(\mu_j(s_t), \sigma^2_{\mathrm{wks}}) \quad \text{with } \mu_j(s) = \delta_0 + \delta_1' s_t + \delta_2' y_j
$$
$$
\mathrm{wks}_{jt} = \begin{cases} \mathrm{wks}^*_{jt} & \text{if} \quad 0 < \mathrm{wks}^*_{jt} < 52 \\ 0 & \text{if} \quad \mathrm{wks}^*_{jt} \leq 0 \\ 52 & \text{if} \quad \mathrm{wks}^*_{jt} \geq 52 \end{cases} \tag{38}
$$

During the unemployment spell, workers may also receive unemployment benefits, proportional to their skills and last occupation j.

$$
\ln b(j; s_t) = b_0 + b_1' s_t + b_2' y_j \tag{39}
$$

The hourly earnings are determined by annual average between wages and unemployment benefits. In other words, workers in occupation j working wks_{jt} obtain the following earnings.

$$
E(j; s_t, e_{jt}, \mathrm{wks}_{jt}) = \frac{\mathrm{wks}_{jt}}{52} w(s_t, j, e_{jt}) + \left(1 - \frac{\mathrm{wks}_{jt}}{52}\right) b(s_t, j) \tag{40}
$$

The identification of unemployment risks can be achieved from the information about the number of weeks worked, which is available in the NLSY97. However, identifying unemployment benefit parameters requires information of unemployment benefit or the model has to be modified so that staying in unemployment is another alternative.

8.2 Decreasing Relative Risk Aversion

Another interesting extension is relative risk aversion varying within individuals, especially depending on their earnings. The conclusion on whether the relative risk aversion varies with earnings is mixed. On one hand, Sahm (2012) utilizes the panel structure of the same hypothetical job choices in the Health and Retirement Survey (HRS) to show that relative risk aversion is not responsive to economic shocks such as unemployment and earnings. On the other hand, the finance literature has documented the evidence of decreasing relative risk aversion (Meeuwis, 2020). The extended model with non-homothetic preference over earnings will enable to test whether relative risk aversion in labor markets also decreases with earnings levels and to evaluate the implications of earnings loss on the future career as well.

To incorporate non-homothetic preferences, workers' utility over earnings is defined by the following ordinary differential equation (ODE):[12]

$$-\frac{u''(E_t;\gamma,\gamma_2)E_t}{u'(E_t;\gamma,\gamma_2)} = \gamma E_t^{-\gamma_2} \tag{41}$$

where γ governs the overall relative risk aversion while γ_2 determines how sensitive the coefficient of relative risk aversion is to earnings. If $\gamma_2 = 0$, the utility takes the form of constant relative risk aversion (CRRA). If $\gamma_2 > 0$, then the relative risk aversion decreases with earnings. Individuals are heterogeneous in risk aversion through varying γ, while γ_2 is common across individuals.

Without the CRRA assumption, hypothetical job choices are no longer reduced into inequalities with respect to relative risk aversion. Therefore, instead of assuming relative risk aversion in hypothetical situations involves noise, I assume idiosyncratic noises in utility comparison. The comparison of utility for the first and the second round can be defined as:

$$U_1^*(W;\gamma_1,\gamma_2) = U_{safe}(W;\gamma_1,\gamma_2) - U_{risky}(W;\gamma_1,\gamma_2)$$

[12] There is no closed form solution of equation (41), so it will be numerically solved in the estimation process. This approach is also adopted in Meeuwis (2020).

$$U_2^*(W;\gamma_1,\gamma_2|g_1) = \begin{cases} U_{safe}(W;\gamma_1,\gamma_2) - U_{more}(W;\gamma_1,\gamma_2) & \text{if } g_1 = 0 \\ U_{safe}(W;\gamma_1,\gamma_2) - U_{less}(W;\gamma_1,\gamma_2) & \text{if } g_1 = 1 \end{cases} \tag{42}$$

With the noise at round l given as $\epsilon_l^g \sim N(0,\sigma_g^2)$, the lottery choice problem at round l becomes determining whether $U_l^* + \epsilon_l^g > 0$. Define the choice variable as $g_l = 1$ if the inequality holds and vice versa. Then, the likelihood of gamble choice can be written as

$$\begin{aligned} &P(g_{i1}, g_{i2}|W_i,\gamma_i,\gamma_2) = P(g_{i1}|W_i,\gamma_i,\gamma_2)P(g_{i2}|W_i,\gamma_i,\gamma_2,g_{i1}) \\ =&\left(\Phi(-U_1^*(W;\gamma_i,\gamma_2)/\sigma_g)^{1-g_{i1}}\Big(1-\Phi(-U_1^*(W;\gamma_i,\gamma_2)/\sigma_g)\Big)^{g_{i1}}\right) \\ &\left(\Phi(-U_2^*(W;\gamma_i,\gamma_2|g_{i1})/\sigma_g)^{1-g_{i2}}\Big(1-\Phi(-U_1^*(W;\gamma_i,\gamma_2|g_{i1})/\sigma_g)\Big)^{g_{i2}}\right) \end{aligned} \tag{43}$$

where Φ represents the cumulative density function (CDF) of standard normal distribution.

9 Conclusion

This paper investigates the influence of heterogeneity in risk aversion on occupation choices and earnings dynamics, recognizing the profound impact of individual risk attitudes on labor market outcomes in the face of pervasive risks inherent in labor market decisions. Occupations are one of the most important sources of earnings and are likely varied in their earnings risks. Self-selection based on risk aversion does affect earnings through on-the-job learning as well as the compensation for risks. This paper provides an empirical framework where risk aversion can have a persistent influence on earnings through occupation choices with differential rates of human capital accumulation.

I first provide descriptive evidence of the significant relationship between risk aversion, earnings dynamics, and occupation choices. Using the survey on the hypothetical job offer choices, I document that individuals with more risk-loving attitudes tend to have higher earnings with higher growth rates over their lives. This pattern is associated with the fact that more risk-averse people on average hold occupations with higher earnings stability and lower profitability, which can be characterized by lower returns and slower growth of earnings.

Building upon the suggestive evidence, I develop a dynamic occupation choice model that allows for heterogeneity in individual risk aversion. Beyond self-selection on risk aversion, an essential mechanism underpinning the effects of risk aversion lies in the interplay between skill accumulation across occupations and occupation-specific returns to skills. Once sorting into different careers, risk-averse workers begin to accrue skills slowly and the impact of diverging skills propagates throughout career trajectories via dynamic selection and switching costs. The model is estimated using the EM algorithm modified to accommodate unobserved heterogeneity and its dynamics. In the decomposition analysis, the estimated model highlights the importance of considering both concurrent compensation to riskier occupations and the dynamic interplay between risk aversion, occupation choices, and unobserved skills.

The empirical framework presented in this paper offers comprehensive insights into the impact of risk preferences on labor market outcomes, while also providing a behavioral perspective on the influence of economic changes on the labor market. The strong association between risk preferences and labor market outcomes suggests that labor market risks are not entirely insurable, prompting workers to leverage their occupation choices as a form of insurance. Future research may extend the model outlined in this paper to incorporate other financial and labor market decisions, such as savings and marriage, and explore the relative importance of occupation choices as a risk mitigation strategy compared to other decision-making contexts.

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Figures and Tables

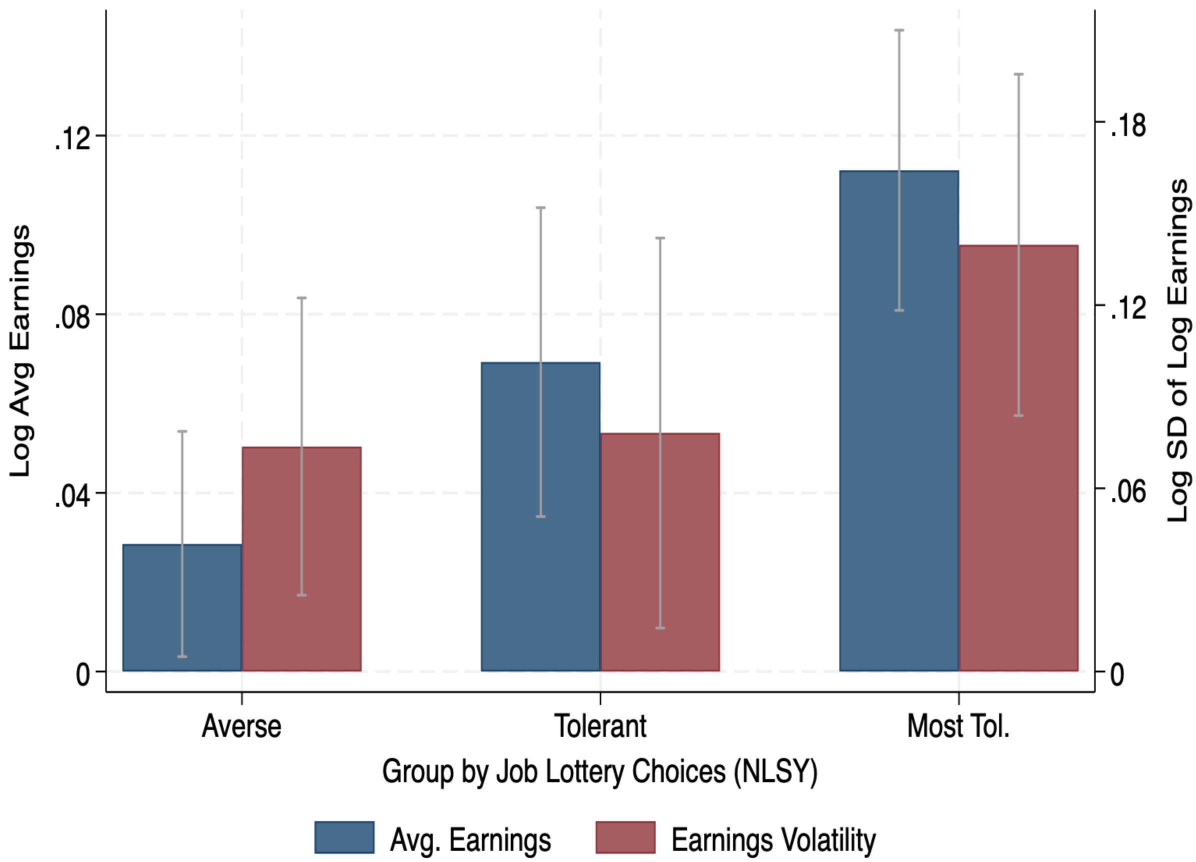


Figure 1: Risk Preferences and Labor Market Outcomes

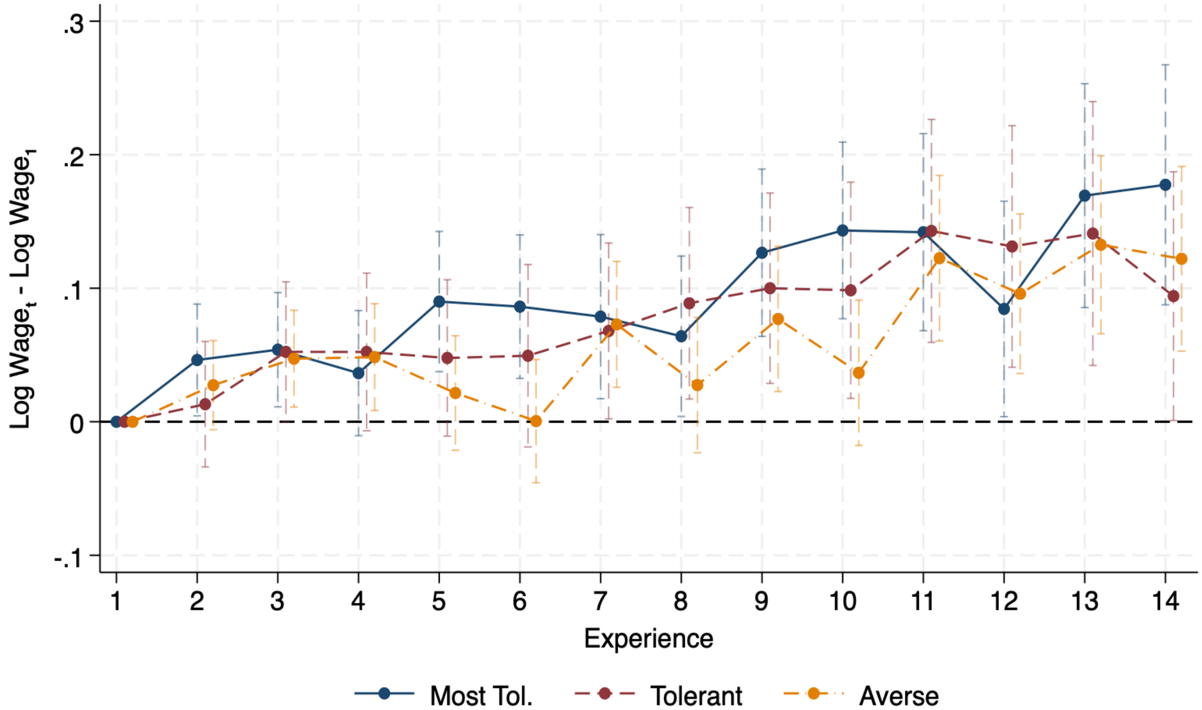


Figure 2: Risk Preferences and Relative Earnings Growth

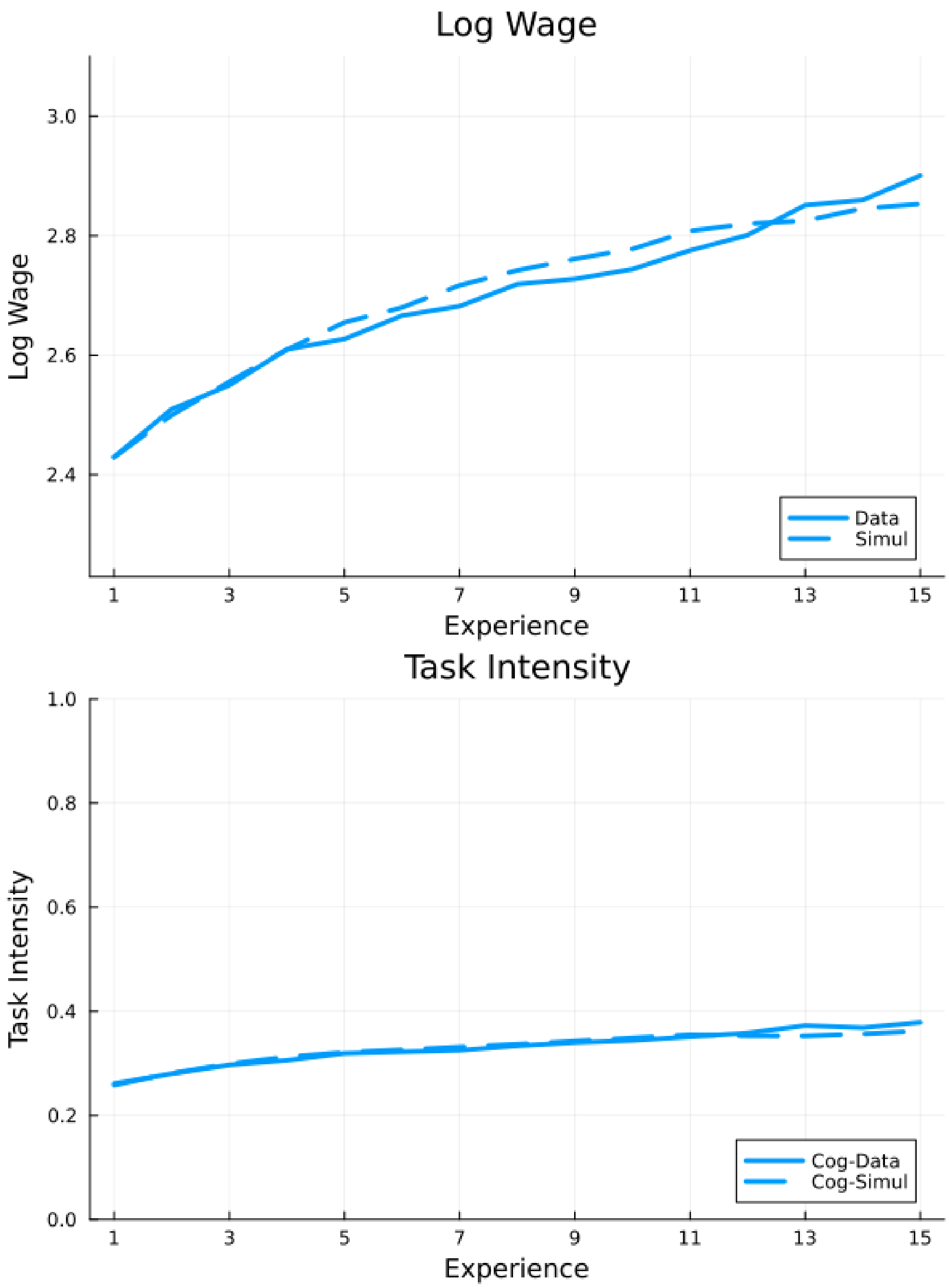


Figure 3: Model Fit

Table 1: Summary Statistics

	Risk Aversion Group				Total
g	1 Most Tol.	2 Tolerant	3 Averse	4 Most Aver.	
	Job Lottery				
Choice	Risky-Risky	Risky-Safe	Safe-Risky	Safe-Safe	
N_{indiv}	673	509	1,027	2,409	4,618
%	15	11	22	52	100
N_{obs}	6,718	5,025	10,193	23,833	45,769
	Demographics				
Black	0.214	0.228	0.235	0.29	0.26
Hispanic	0.184	0.171	0.206	0.209	0.201
Men	0.63	0.558	0.524	0.473	0.516
Education	13.88	14.037	13.883	13.176	13.531
AFQT	0.193	0.258	0.156	-0.107	0.036
	Labor Market Outcomes				
Log Earnings (per hours)	2.91	2.89	2.827	2.716	2.788
Weeks Worked (per year)	45.608	45.75	45.43	44.45	44.981
Earnings Stability	0.473	0.491	0.506	0.519	0.506
Profitability	0.606	0.607	0.572	0.529	0.559

Source.–National Longitudinal Survey of Youth 1997.

Table 2: Risk Aversion and Lifetime Earnings (Base: Most Averse)

	Log Average Earnings			Log SD of Log Earnings		
	(1)	(2)	(3)	(4)	(5)	(6)
Most Tolerant	0.112***	0.166***	0.165***	0.140***	0.152***	0.147***
	(0.016)	(0.034)	(0.033)	(0.029)	(0.057)	(0.057)
Tolerant	0.069***	0.098**	0.092**	0.078**	0.107*	0.103*
	(0.018)	(0.039)	(0.039)	(0.033)	(0.063)	(0.062)
Averse	0.029**	0.046	0.045	0.074***	0.087*	0.082
	(0.013)	(0.028)	(0.028)	(0.025)	(0.051)	(0.051)
Demographics	✓	✓	✓	✓	✓	✓
Non-cognitive			✓			✓
Parent income 97			✓			✓
N	4,960	1,047	1,047	4,936	1,046	1,046
R^2	0.362	0.375	0.383	0.042	0.083	0.092

Source.–National Longitudinal Survey of Youth 1997

Notes.–The estimates are from the regression of lifetime average and volatility of earnings on risk attitude group indicators. Control variables include race, gender, age-adjusted AFQT scores and education level. The second column restricts the sample to individuals whose non-cognitive skill measures and parent income in 1997 are available. Non-cognitive skill measures include social skill measures and noncognitive skill measures constructed using Goldberg's Big Five personal factor survey. Robust standard errors in parenthesis.

Table 3: Risk Aversion and Occupation Choice

	Earnings Stability (SD)			Profitabitliy (SD)		
	(1)	(2)	(3)	(4)	(5)	(6)
Most Tolerant	-0.107***	-0.131***	-0.133***	0.103***	0.195***	0.198***
	(0.023)	(0.047)	(0.047)	(0.025)	(0.049)	(0.049)
Tolerant	-0.076***	-0.022	-0.023	0.062**	0.087	0.081
	(0.029)	(0.062)	(0.062)	(0.028)	(0.059)	(0.058)
Averse	-0.060***	-0.086*	-0.087*	0.011	0.096**	0.096**
	(0.022)	(0.046)	(0.047)	(0.022)	(0.045)	(0.045)
Demographics	✓	✓	✓	✓	✓	✓
Noncog			✓			✓
Parent Income at 97			✓			✓
N	49,453	10,867	10,867	49,453	10,867	10,867
R^2	0.026	0.038	0.038	0.263	0.286	0.287

Source.–National Longitudinal Survey of Youth 1997

Note.–The estimates are from the regression of average task intensity, earnings risk measures, and occupational average of wages on risk attitude group indicators. Control variables include race, gender, age-adjusted AFQT scores and education level indicators. Standard errors clustered at individual-occupation level.

Table 4: Regression of Log Earnings on History of Occupational Quality

Log Earnings, t	All	High School	College
Earnings Stability (SD), $t-1$	0.004	0.007	0.001
	(0.004)	(0.005)	(0.007)
Profitability (SD), $t-1$	0.020***	0.022***	0.016***
	(0.004)	(0.005)	(0.006)
Current Occ FEs	✓	✓	✓
Indiv FEs & Year Fes	✓	✓	✓
Covariates	✓	✓	✓
N	40,184	25,029	15,152
R^2	0.701	0.621	0.724

Source.–National Longitudinal Survey of Youth 1997

Note.–The estimates are from the regression of log earnings on task intensity indices at the last period. Control variables include cubic experience profiles, current occupation, individual, and year fixed effects. Standard errors clustered at the individual-occupation level.

Table 5: Inequality Conditions for Lottery Choice

Group	g	Choice	Lower bound	Upper bound
Most Tolerant	$(0,0)$	Risky-More Risky	0	1
Tolerant	$(0,1)$	Risky-Safe	1	2
Averse	$(1,0)$	Safe-Less Risky	2	3.76535
Most Averse	$(1,1)$	Safe-Safe	3.76535	∞

Table 6: Uncertainty and Wage Parameters

	Wage			Risk	
	Estimate	Standard Error		Estimate	Standard Error
π_0	2.34	0.009	a_0	0.234	0.004
π_1	0.34	0.018	a_1	0.041	0.01
q_0	0.182	0.005	c_0	1.012	0.028
q_1	0.047	0.005	c_1	0.232	0.032

Source.–National Longitudinal Survey of Youth 1997

Note.–The estimates are for wage and risk parameters. The wage equation is $\ln w(s_t, j) = \pi_0+\pi_1' y_j+(q_0+Q_1' y_j)s_t+\sigma(y_j)e_t$ where $e_t \sim N(0,1)$. $\sigma(y) = a_0+a_1' y$ and $s(y) = c_0+C_1' y$ where $\sigma(y)$ is transitory risks and ζs are persistent risks. a_{1k} is the element of a_1 corresponding to task k. $C_1(\cdot, k)$ refers to the coefficients on each task in the function of k-task persistent risks.

Table 7: Skill and Preference Parameters

	Skill			Preference	
	Estimate	Standard Error		Estimate	Standard Error
d_0	-0.002	0.018	f_0	-5.15	0.087
d_{11}	0.776	0.01	$F_{1,\text{Black}}$	-0.322	0.05
d_{12}	0.019	0.002	$F_{1,\text{Male}}$	0.16	0.045
d_2	0.598	0.021	$F_{1,\text{AFQT}}$	0.227	0.042
$d_{3,\text{Black}}$	-0.105	0.019	F_2	3.852	0.134
$d_{3,\text{Male}}$	0.198	0.017	f_3	0.234	0.002
$d_{3,\text{AFQT}}$	0.099	0.016	F_4	-16.184	0.196
			$\overline{y}_0$	0.147	0.015
	Initial Skill		$Y_{1,\text{Black}}$	-0.036	0.012
$H_{1,\text{Black}}$	-0.243	0.059	$Y_{1,\text{Male}}$	0.049	0.011
$H_{1,\text{Male}}$	0.221	0.054	$Y_{1,\text{AFQT}}$	0.013	0.011
$H_{1,\text{AFQT}}$	0.158	0.055	$Y_{1,\gamma}$	0.015	0.002
$H_{1,\gamma}$	-0.028	0.013			

Source.–National Longitudinal Survey of Youth 1997

Note.–The estimates are for skill formation and preference parameters. The skill transition equation is $s_{t+1}(x, s_t, j) = d_0 + d_{11}s_t + d_{12}s_t^2 + d_2 y_j + d_3 x + \eta_t(y_j)$. Initial skill equation is $s_1 = h_0 + H_1(x', \gamma)' + \xi$. The preference equation is $C(j; s_t, x, j_{t-1}) = (f_0 + F_1 x + F_2 y_j + f_3 s_t +)' y_j - (y_{j_{t-1}} - y_j)' F_4 (y_{j_{t-1}} - y_j)$. Initial task equation is $y_0 = \overline{y}_0 + Y_1 x$.

Table 8: Earnings Gap Decomposition - Log Lifetime Earnings Relative to Most Averse

	Data	Baseline	No Initial Het.	No Move Cost	No Learn Het.
Most Tolerant	0.106	0.192	0.186	0.151	0.044
% of Baseline		(100)	(97)	(77)	(23)
Tolerant	0.098	0.036	0.013	0.016	0.007
% of Baseline		(100)	(37)	(44)	(19)
Averse	0.029	0.006	-0.005	0.002	0.001
% of Baseline		(100)	(-83)	(33)	(17)

Note.–The table reports the estimates of the regression of log lifetime average earnings on risk attitude group indicators using the real data and the data simulated with the estimated parameters in Table 6 and Table 7 and their variations. The simulated data are 5 times the size of the real data. The percent of the earnings gap relative to the baseline is reported in the parenthesis. A detailed description of the simulations is provided in Section 7.

A Maximization Stage in the EM algorithm

In this section, I show that maximizing a logarithm of the weighted summed likelihood, which integrates out all unobserved state variables, is equivalent to maximizing a weighted sum of log-likelihood, where the weight is the conditional probability of an individual being in an unobserved state. For simplicity, assume that only initial skills are heterogeneous and remain the same. Also, define $\theta_{-u} = (\theta_r, \theta_w, \theta_p)$, the model parameters other than the distribution of unobserved states (θ_u). Given the estimated CCPs and the distribution of unobserved heterogeneity, θ_{-u} can be updated by maximizing:

$$LL(\theta_{-u}) = \sum_i \log L(g_i, Z_i|x_i; \hat{P}, \theta_u, \theta_{-u}) \tag{A.1}$$

where

$$L(g_i, Z_i|x_i; \hat{P}, \theta_u, \theta_{-u}) = \sum_{\gamma \in \{\gamma_H, \gamma_L\}} P(\gamma|x_i; \theta_u)\mathcal{L}(g_i, Z_i|\gamma, x_i; \hat{P}, \theta_u, \theta_{-u}) \tag{A.2}$$

For exposition, $\hat{P}$ and θ_u are omitted henceforth. The first order condition of maximizing (A.1) is

$$\begin{aligned} 0 &= \sum_i \frac{1}{L(g_i, Z_i|x_i; \theta_{-u})} \sum_\gamma P(\gamma|x_i) \frac{\partial}{\partial \theta_{-u}} \mathcal{L}(g_i, Z_i|\gamma, x_i; \theta_{-u}) \\ &= \sum_i \sum_\gamma \frac{P(\gamma|x_i)\mathcal{L}(g_i, Z_i|\gamma, x_i; \theta_{-u})}{L(g_i, Z_i|x_i; \theta_{-u})} \frac{\partial}{\partial \theta} \log \mathcal{L}(g_i, Z_i|\gamma, x_i; \theta_{-u}) \\ &= \sum_i \sum_\gamma p_{1i}(\gamma) \frac{\partial}{\partial \theta_{-u}} \log \mathcal{L}(g_i, Z_i|\gamma, x_i; \theta_{-u}) \end{aligned} \tag{A.3}$$

where $p_{1i}(\gamma)$ represents the conditional probability of individual i being risk aversion type γ.

Given $p_{1i}(\cdot)$, maximizing (A.1) is equivalent to maximizing the following likelihood function since they have the same first-order condition.

$$\begin{aligned}\hat{LL}(\theta_{-u}) &= \sum_i \sum_\gamma p_{1i}(\gamma) \log \mathcal{L}(g_i, Z_i|\gamma, x_i; \theta_{-u}) \\ &= \sum_i \sum_\gamma p_{1i}(\gamma)\big(\log l^*(Z_i|\gamma, x_i; \theta_{-u}) + \log P(g_i|\gamma, Z_i; \theta_r)\big) \end{aligned} \tag{A.4}$$

Since the likelihood is additively separable, the parameters can be estimated in stages. θ_r is first estimated from:

$$\hat{\theta}_r = \arg\max_{\theta_r} \sum_i \sum_\gamma p_{1i}(\gamma) \log P(g_i|\gamma, Z_i; \theta_r) \tag{A.5}$$

Given $\hat{\theta}_r$, the rest of the parameters (θ_w, θ_p) can be recovered from maximizing the following.

$$\begin{aligned}&\sum_i \sum_\gamma p_{1i}(\gamma) \log l^*(Z_i|\gamma, x_i; (\hat{\theta}_r, \theta_w, \theta_p)) \\ &= \sum_i \sum_\gamma p_{1i}(\gamma) \log \left(\sum_s \pi(s|x_i) l(Z_i|s, \gamma, x_i; (\hat{\theta}_r, \theta_w, \theta_p)) \right) \end{aligned} \tag{A.6}$$

The first-order condition of maximizing (A.6) can be written as

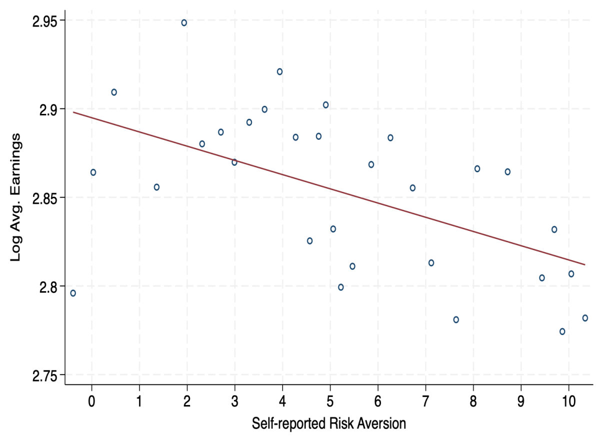
$$\begin{aligned} 0 &= \sum_i \sum_\gamma p_{1i}(\gamma) \frac{1}{l^*(Z_i|\gamma, x_i; (\hat{\theta}_r, \theta_w, \theta_p),)} \sum_s \pi(s|x_i) \frac{\partial}{\partial \theta_{w,p}} l(Z_i|s, \gamma, x_i; \hat{P}, (\hat{\theta}_r, \theta_w, \theta_p)) \\ &= \sum_i \sum_\gamma p_{1i}(\gamma) \sum_s \frac{\pi(s|x_i) l(Z_i|s, \gamma, x_i; \hat{P}(\hat{\theta}_r, \theta_w, \theta_p))}{l^*(Z_i|\gamma, x_i; \hat{P}(\hat{\theta}_r, \theta_w, \theta_p))} \frac{\partial}{\partial \theta_{w,p}} \log l(Z_i|s, \gamma, x_i; (\hat{\theta}_r, \theta_w, \theta_p)) \\ &= \sum_i \sum_\gamma \sum_s p_{1i}(\gamma) p_{2i}(s|\gamma) \frac{\partial}{\partial \theta_{w,p}} \log l(Z_i|s, \gamma, x_i; (\hat{\theta}_r, \theta_w, \theta_p)) \end{aligned} \tag{A.7}$$

where $p_{2i}(s|\gamma)$ refers to the conditional probability of individual i being in unobserved state s given γ. In other words, given $p_{1i}(\gamma), p_{2i}(s|\gamma)$, and $\hat{\theta}_r$, maximizing (A.6) is equivalent to the following optimization problem.

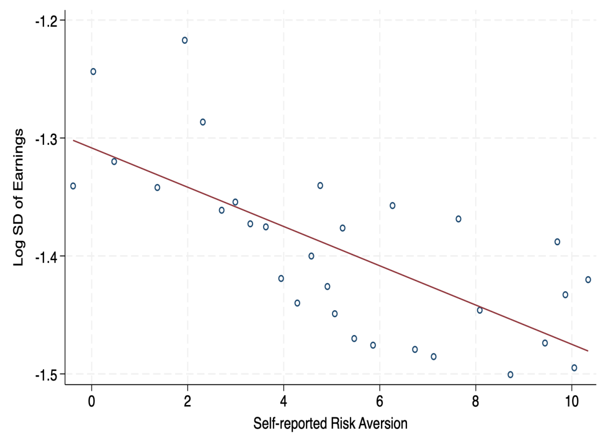
$$(\hat{\theta_w}, \hat{\theta_p}) = \arg\max_{(\theta_w, \theta_p)} \sum_i \sum_\gamma \sum_s p_{1i}(\gamma) p_{2i}(s|\gamma) \log l(Z_i|s, \gamma, x_i; (\hat{\theta}_r, \theta_w, \theta_p)) \tag{A.8}$$

The log-likelihood of occupation choice and wage is again additively separable, so wage parameters and nonpecuniary parameters can be separately estimated in stages. Extending the setting into dynamic skill transition is straightforward as suggested by Arcidiacono and Miller (2011).

Additional Figures and Tables



(a) Lifetime Average Earnings



(b) Lifetime Earnings Volatility

Figure A1: Self-reported Risk Attitudes and Labor Market Outcomes

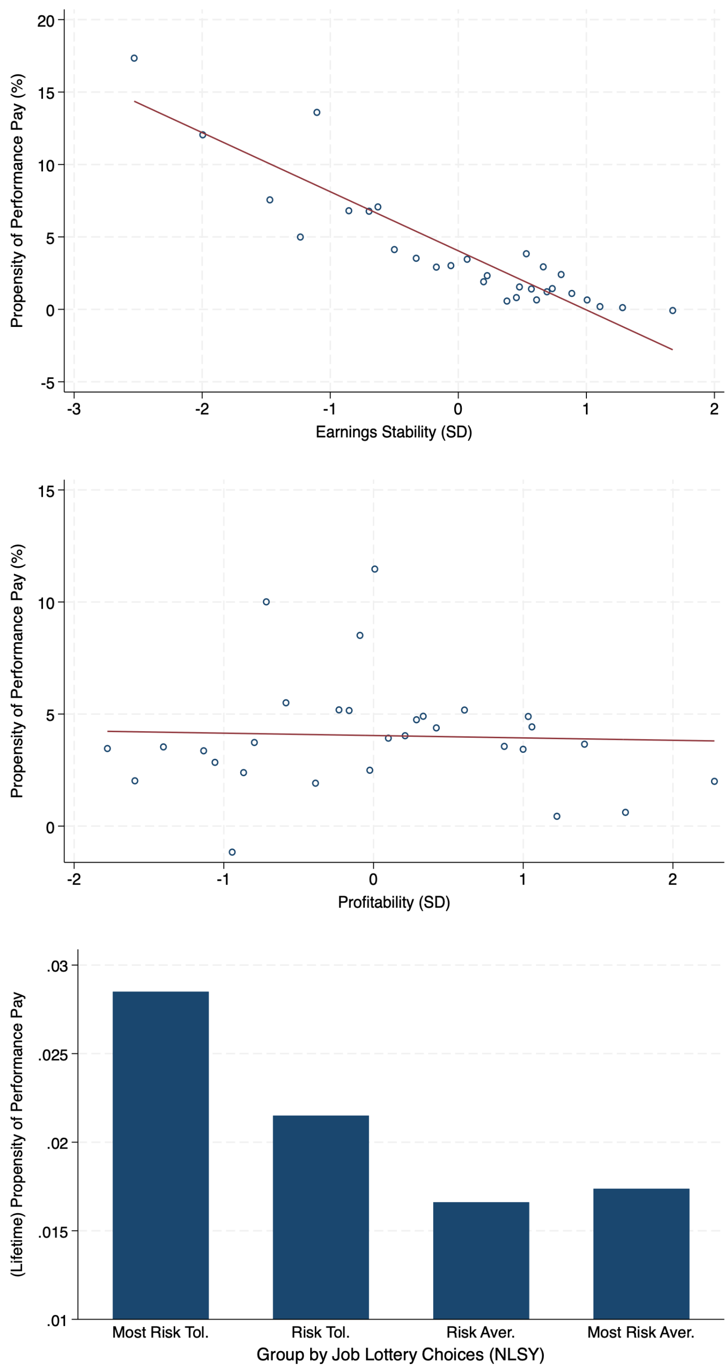


Figure A2: Performance Pay, Earnings Risks, and Risk Aversion

Table A1: Adaptive Lasso Regression

Earnings Stability	
Communicating with Supervisors, Peers, or Subordinates	0.038
Thinking Creatively	-0.027
Degree of Automation	0.025
Selling or Influencing Others	-0.021
Mathematics	0.017
Spend Time Walking or Running	0.013
Number Facility	0.009
Dealing with Physically Aggressive People	0.007
Monitor Processes, Materials, and Surroundings	0.006
R^2	0.644
Profitability	
Critical Thinking	0.111
Level of Competition	0.106
Analyzing Data and Information	0.083
Impact of Decisions on Coworkers or Company Results	0.063
R^2	0.795

Source.–National Longitudinal Survey of Youth 1997 and Occupational Information Network.

Table A2: Risk Aversion, Lifetime Earnings and Occupations (Base: Most Averse)

	Log Average Earnings			Log SD of Log Earnings		
	(1)	(2)	(3)	(4)	(5)	(6)
Most Tolerant	0.115***	0.092***	0.083***	0.122***	0.106***	0.100***
	(0.016)	(0.015)	(0.015)	(0.027)	(0.027)	(0.027)
Tolerant	0.061***	0.058***	0.059***	0.053*	0.052*	0.044
	(0.018)	(0.017)	(0.016)	(0.030)	(0.030)	(0.030)
Averse	0.042***	0.034***	0.031***	0.043*	0.033	0.025
	(0.013)	(0.012)	(0.012)	(0.024)	(0.024)	(0.024)
Demographics	✓	✓	✓	✓	✓	✓
Major Occupation		✓	✓		✓	✓
2nd Major Occupation			✓			✓
N	4,183	4,183	4,183	4,173	4,173	4,173
R^2	0.358	0.474	0.521	0.048	0.102	0.123

Source.–National Longitudinal Survey of Youth 1997

Notes.–The estimates are from the regression of lifetime average and volatility of earnings on risk attitude group indicators. Control variables include race, gender, and AFQT scores. Robust standard errors in parenthesis.

Table A3: Quality Measure and Occupational Characteristics by 2-digit Occupations

	Earn. Stab.		Profit.		Earn. Risk		Mean. Wage	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Management	0.512	0.242	0.892	0.053	0.245	0.046	3.333	0.124
Buss/Finance	0.752	0.124	0.836	0.037	0.223	0.032	3.275	0.077
Computer/Math	0.514	0.083	0.891	0.067	0.263	0.129	3.502	0.178
Engineer	0.576	0.115	0.877	0.095	0.204	0.006	3.293	0.312
Physical/Social Science	0.506	0.305	0.85	0.115	0.215	0.048	3.144	0.164
Social Services	0.207	0.163	0.625	0.112	0.312	0.149	2.823	0.182
Legal	0.367	0.287	0.841	0.172	0.25	0.091	3.371	0.49
Educ	0.265	0.149	0.507	0.277	0.235	0.085	2.808	0.252
Arts	0.048	0.052	0.772	0.054	0.389	0.053	3.112	0.084
Healthcare	0.517	0.251	0.838	0.14	0.223	0.051	3.206	0.407
Health Supp	0.485	0.172	0.366	0.174	0.212	0.035	2.706	0.21
Protective	0.619	0.216	0.7	0.178	0.195	0.04	3.032	0.27
Food Service	0.319	0.177	0.114	0.216	0.226	0.06	2.481	0.192
Clean	0.21	0.086	0.257	0.211	0.326	0.055	2.717	0.286
Personal	0.231	0.199	0.323	0.174	0.317	0.116	2.691	0.272
Sales	0.29	0.286	0.543	0.345	0.265	0.084	2.947	0.376
Administrative	0.845	0.128	0.406	0.131	0.169	0.019	2.759	0.13
Farm	0.15		0.039		0.343		2.46	
Construct	0.387	0.071	0.554	0.054	0.219	0.046	3.065	0.272
Repair	0.194	0.157	0.64	0.073	0.239	0.089	3.069	0.205
Produce	0.715	0.271	0.299	0.136	0.189	0.075	2.68	0.197
Transportation	0.671	0.177	0.344	0.153	0.239	0.037	2.82	0.156
All	0.508	0.299	0.558	0.276	0.238	0.071	2.938	0.316

Source.–Occupational Information Network, National Longitudinal Survey of Youth 1997

Table A4

SOC3	Title	SOC3 New	Title
111	Top Executives	111	Top Executives
112	Advertising and Sales Managers	112	Advertising and Sales Managers
113	Operations Specialties Managers	113	Operations Specialties Managers
119	Other Management Occupations	119	Other Management Occupations
131	Business Operations Specialists	131	Business Operations Specialists
132	**Financial Specialists**	**131**	**Business Operations Specialists**
151	Computer Occupations	151	Computer Occupations
152	**Mathematical Science Occupations**	**192**	**Physical Scientists**
172	Engineers	172	Engineers
173	Drafters, Engineering Technicians, and Mapping Technicians	173	Drafters, Engineering Technicians, and Mapping Technicians
191	**Life Scientists**	**192**	**Physical Scientists**
192	Physical Scientists	192	Physical Scientists
193	Social Scientists and Related Workers	193	Social Scientists and Related Workers
194	Life, Physical, and Social Science Technicians	194	Life, Physical, and Social Science Technicians
211	Other Community and Social Service Specialists	211	Other Community and Social Service Specialists
212	**Religious Workers**	**211**	**Other Community and Social Service Specialists**
231	Lawyers, Judges, and Related Workers	231	Lawyers, Judges, and Related Workers
232	Legal Support Workers	232	Legal Support Workers
251	**Postsecondary Teachers**	**253**	**Other Teachers and Instructors**
252	**Preschool, Elementary, Middle Education Teachers**	**253**	**Other Teachers and Instructors**
253	Other Teachers and Instructors	253	Other Teachers and Instructors
254	**Librarians, Curators, and Archivists**	**259**	**Other Educational Instruction and Library Occupations**
259	Other Educational Instruction and Library Occupations	259	Other Educational Instruction and Library Occupations
271	Art and Design Workers	271	Art and Design Workers
272	Entertainers and Performers, Sports and Related Workers	272	Entertainers and Performers, Sports and Related Workers
273	Media and Communication Workers	273	Media and Communication Workers
274	Media and Communication Equipment Workers	274	Media and Communication Equipment Workers
291	Healthcare Diagnosing or Treating Practitioners	291	Healthcare Diagnosing or Treating Practitioners
292	Health Technologists and Technicians	292	Health Technologists and Technicians
311	**Health and Personal Care Aides**	**312**	**Occupational and Physical Therapist Assistants**
312	Occupational and Physical Therapist Assistants	312	Occupational and Physical Therapist Assistants
331	Supervisors of Protective Service Workers	331	Supervisors of Protective Service Workers
332	**Firefighting and Prevention Workers**	**333**	**Law Enforcement Workers**
333	Law Enforcement Workers	333	Law Enforcement Workers
339	Other Protective Service Workers	339	Other Protective Service Workers
351	Supervisors of Food Preparation and Serving Workers	351	Supervisors of Food Preparation and Serving Workers
352	Cooks and Food Preparation Workers	352	Cooks and Food Preparation Workers
353	**Food and Beverage Serving Workers**	**359**	**Other Food Preparation and Serving Related Workers**
359	Other Food Preparation and Serving Related Workers	359	Other Food Preparation and Serving Related Workers
371	Supervisors of Cleaning and Maintenance Workers	371	Supervisors of Cleaning and Maintenance Workers
372	Building Cleaning and Pest Control Workers	372	Building Cleaning and Pest Control Workers
373	Grounds Maintenance Workers	373	Grounds Maintenance Workers
392	**Animal Care and Service Workers**	**399**	**Other Personal Care and Service Workers**
393	Entertainment Attendants and Related Workers	393	Entertainment Attendants and Related Workers
395	Personal Appearance Workers	395	Personal Appearance Workers
396	**Baggage Porters, Bellhops, and Concierges**	**399**	**Other Personal Care and Service Workers**
399	Other Personal Care and Service Workers	399	Other Personal Care and Service Workers
411	Supervisors of Sales Workers	411	Supervisors of Sales Workers
412	Retail Sales Workers	412	Retail Sales Workers
413	Sales Representatives, Services	413	Sales Representatives, Services
414	**Sales Representatives, Wholesale and Manufacturing**	**413**	**Sales Representatives, Wholesale and Manufacturing**
419	Other Sales and Related Workers	419	Other Sales and Related Workers

Table A4 continued from previous page

SOC3	Title	SOC3 New	Title
431	Supervisors of Office and Administrative Support Workers	431	Supervisors of Office and Administrative Support Workers
432	Communications Equipment Operators	432	Communications Equipment Operators
433	**Financial Clerks**	**434**	**Information and Record Clerks**
434	Information and Record Clerks	434	Information and Record Clerks
435	Material Recording and Distributing Workers	435	Material Recording and Distributing Workers
436	**Secretaries and Administrative Assistants**	**439**	**Other Office and Administrative Support Workers**
439	Other Office and Administrative Support Workers	439	Other Office and Administrative Support Workers
452	Agricultural Workers	452	Agricultural Workers
471	**Supervisors of Construction and Extraction Workers**	**511**	**Supervisors of Production Workers**
472	Construction Trades Workers	472	Construction Trades Workers
473	**Helpers, Construction Trades**	**472**	**Construction Trades Workers**
474	**Other Construction and Related Workers**	**472**	**Construction Trades Workers**
475	**Extraction Workers**	**472**	**Construction Trades Workers**
491	**Supervisors of Installation, Maintenance, and Repair Workers**	**511**	**Supervisors of Production Workers**
492	**Electrical and Electronic Equipment Mechanics, Installers, and Repairers**	**499**	**Other Installation, Maintenance, and Repair Occupations**
493	**Vehicle and Mobile Equipment Mechanics, Installers, and Repairers**	**499**	**Other Installation, Maintenance, and Repair Occupations**
499	Other Installation, Maintenance, and Repair Occupations	499	Other Installation, Maintenance, and Repair Occupations
511	Supervisors of Production Workers	511	Supervisors of Production Workers
512	Assemblers and Fabricators	512	Assemblers and Fabricators
513	Food Processing Workers	513	Food Processing Workers
514	Metal Workers and Plastic Workers	514	Metal Workers and Plastic Workers
515	Printing Workers	519	Other Production Occupations
516	Textile, Apparel, and Furnishings Workers	516	Textile, Apparel, and Furnishings Workers
517	**Woodworkers**	**516**	**Textile, Apparel, and Furnishings Workers**
519	Other Production Occupations	519	Other Production Occupations
531	**Supervisors of Transportation and Material Moving Workers**	**511**	**Supervisors of Production Workers**
533	Motor Vehicle Operators	533	Motor Vehicle Operators
536	Other Transportation Workers	536	Other Transportation Workers
537	Material Moving Workers	537	Material Moving Workers