Risk Aversion, Occupation Choice, and Earnings Dynamics*

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Abstract

This paper examines how differences in risk aversion influence occupational choices and the distribution of earnings. I first show that more risk-averse workers earn significantly less, and that this earnings gap widens over time. A key driver of this pattern is that risk-averse individuals tend to select occupations with more stable, but lower, earnings and slower earnings growth. To quantify the importance of this channel and distinguish it from sorting based on unobserved traits, I develop and estimate a structural model of occupation choice that accounts for heterogeneity in risk aversion and human capital accumulation. In the model, risk aversion is correlated with both observed and unobserved initial skills, and it influences skill accumulation through occupational choices. Using the estimated model on the non-college sample, I perform a decomposition analysis showing that 30 percent of the earnings gap between the most and least risk-averse workers (14 log points) can be explained by occupation choices. Of this, approximately 55 percent is due to lower pay in safer occupations, while the remaining 45 percent is attributable to slower human capital accumulation. In a counterfactual analysis, I find that social insurance providing an earnings floor enables risk-averse workers to select into relatively higher-return occupations, reducing the earnings gap between risk-tolerant and risk-averse workers by around 29 percent (4 log points). Similar patterns are observed in the college sample.

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1 Introduction

Risk preferences are a crucial factor in decision-making under uncertainty.[1] In labor markets, workers encounter occupation-specific risks when making career choices.[2] For example, roles in sales and finance may offer higher average returns but are subject to greater earnings volatility due to market fluctuations, whereas public sector jobs tend to provide more stable, but lower, earnings. This indicates that heterogeneity in risk aversion, combined with varying occupational risks, can contribute to inequality in labor market outcomes.

Despite its theoretical importance, empirical research on the relationship between risk aversion and labor market inequalities remains limited, primarily due to two key challenges. First, few datasets contain both detailed career histories and individual-level measures of risk aversion. Second, occupation choices affect not only immediate earnings but also the accumulation of human capital, potentially amplifying the long-term effects of these decisions. To fully understand how risk aversion shapes occupational choices and labor market outcomes, an empirical framework is needed that captures the dynamic interaction between risk aversion and human capital accumulation.

In this paper, I estimate the causal effect of heterogeneity in risk aversion on occupational choices and earnings profiles. Using data from the National Longitudinal Survey of Youth 1997 (NLSY97), which includes hypothetical gamble responses as well as detailed employment histories, I first show that risk-averse workers earn less than risk-tolerant workers, and this gap widens over time. The evidence suggests that this pattern is driven by risk-averse workers sorting into occupations with lower earnings volatility, levels, and growth rates. I then develop and estimate a dynamic occupation choice model where workers differ in both initial skills and risk aversion,

[1] Seminal theoretical contributions on risk preferences include Neumann and Morgenstern (1947), Arrow (1965), and Pratt (1964). Empirical studies such as Barsky et al. (1997) and Dohmen and Falk (2011) document significant relationships between risk attitudes and decisions like smoking, insurance uptake, and asset allocation.

[2] Hartog and Vijverberg (2007) and Bonin et al. (2007) document that the cross-section variance of earnings conditional on observed worker characteristics varies across occupations. Dillon (2018) measures lifetime earnings risks, accounting for wage risks, employment risks, and endogenous job mobility, and shows that these risks significantly vary by initial occupations.

and select occupations that vary not only in terms of risks and returns but also in the human capital formation they facilitate. While more risk-averse workers may select safer occupations, these occupations may provide slower human capital growth. This approach allows me to quantify the impact of risk aversion on earnings, distinguishing it from initial heterogeneity in observed and unobserved characteristics, and to decompose the effect into a contemporaneous component (safer occupations may pay less) and a dynamic component (safer jobs may foster slower skill accumulation). Finally, I use the model to assess the distributional implications of a social insurance program that provides an earnings floor, focusing on how it influences occupational sorting and the resulting earnings disparities across workers with different degrees of risk aversion.

I use the detailed annual information from the NLSY97 on individuals' occupations, earnings, and personal characteristics, such as demographics, cognitive ability (AFQT scores), and family background. I leverage responses to hypothetical income gambles to classify individuals into four groups of risk attitudes. Additionally, I characterize each occupation using two key measures—earnings returns and earnings stability—as risk-averse individuals consider both expected returns and earnings risk when selecting occupations.

I first present that more risk-tolerant individuals experience higher overall earnings, larger earnings volatility, and faster earnings growth. Compared to the most risk-averse group, the most tolerant group has 11 percent higher lifetime earnings and 14 percent higher earnings volatility, and experiences 18 percentage points more earnings growth over 14 years of experience, conditional on observed characteristics. Next, I provide suggestive evidence that occupational sorting driven by risk aversion can explain the relationship between risk aversion and earnings: (1) more risk-averse workers tend to choose occupations with lower returns but more stable earnings, and (2) selecting lower-return occupations is also associated with slower future earnings growth even conditional on having the same occupation in the future.

While the descriptive evidence provides suggestive support, quantifying the causal impact of risk aversion on earnings through occupation choices requires accounting for its interaction with unobserved human capital. Risk aversion influences human capital through two key channels. First, it may be correlated with unobserved initial skills, as it shapes pre-market decisions—such as internships—that determine skill endowments. Second, the accumulation of skills varies across occupations, meaning that risk aversion can lead to divergent skill trajectories as individuals make different occupation choices depending on their risk preferences. This dynamic reinforces the impact of risk aversion on earnings over time. Given that human capital is unobserved, identifying the role of occupation selection in the effects of risk aversion requires a model that imposes assumptions on the initial skill distribution and its evolution.

I develop an occupational choice model that incorporates heterogeneity in risk aversion and its interaction with unobserved skills. Workers begin their careers with varying initial skills, risk aversion, and observable traits (e.g., gender, race, AFQT scores). Each period, workers select an occupation from a discrete set of options, where occupations differ in terms of expected returns and earnings stability. These factors influence the distribution of productivity shocks and the rate of skill accumulation. The combination of worker characteristics and occupation-specific features influences both the pecuniary returns and the non-pecuniary value of each occupation.

I estimate the model using data from the non-college and college graduate sample of the NLSY97 separately. I assume that members of each risk attitude group share a common level of relative risk aversion. Following Kimball et al. (2009), I estimate a log-normal distribution of risk tolerance using hypothetical lottery choices and calculate the conditional expected values of risk aversion coefficients for each group. To account for time-varying unobserved heterogeneity in skills, I use the expectation-maximization (EM) algorithm in combination with the conditional choice probability (CCP) estimator to estimate the remaining model parameters, following Arcidiacono and Miller (2011).

The parameter estimates reveal three key patterns. First, occupational risks vary widely: the standard deviations of transitory wage shocks range from 0.1 to 0.4 across occupations, while those of persistent skill shocks range from 0.1 to 0.16, assuming an average skill price. These differences in earnings risk suggest that risk-averse individuals tend to select occupations with lower shock variances. Second, skill accumulation is generally higher in occupations with higher returns, indicating that career choices can lead to diverging skill trajectories over time. Finally, among non-college workers, the most risk-tolerant individuals have initial skills about 0.23 standard deviations higher than their most risk-averse counterparts, equivalent to 8 percent higher initial earnings at average skill price. For college graduates, the initial skill difference is 0.42 standard deviations, translating to approximately 16 percent higher initial earnings. This correlation highlights the importance of accounting for unobserved heterogeneity when examining the role of risk aversion in occupational choices and earnings.

Using the estimated model, I conduct a decomposition analysis to quantify how risk aversion impacts earnings through distinct channels. I start with the estimated model to simulate earnings trajectories and occupation choices as a baseline. Holding occupation choices constant at baseline values throughout, I sequentially remove initial heterogeneity—both observed and unobserved—and differences in occupation-specific skill accumulation. In the non-college sample, differences in occupational selection explain 30 percent (4.2 log points) of the 14-log-point (unconditional) earnings gap between the most and least risk-tolerant, with the remaining gap due to initial heterogeneity. Divergent human capital accumulation accounts for 45 percent (1.9 log points) of the occupational effect. Among college graduates, occupational choice explains 33 percent of the 23.5-log-point gap, with 48 percent of this effect driven by differences in skill accumulation across occupations.

As a final exercise, I evaluate the distributional impact of a social insurance program that sets an earnings floor for workers. The impact of this intervention depends on how risk-averse workers respond and the distribution of risk aversion across the economy. To analyze its differential impacts on occupation choices and earnings for risk-averse individuals, I simulate workers' career choices under an earnings floor policy. The hourly earnings floor is set at $9.3, representing 60 percent of the median earnings of the sample.

The results reveal that introducing an earnings floor reduces the earnings disparity between risk-tolerant and risk-averse workers by approximately 30 percent in both samples, resulting in a 4-log-point reduction in the non-college group and a 5-log-point reduction in the college group. This reduction stems primarily from differential occupation adjustments according to differing risk preferences. Risk-tolerant workers move toward occupations with lower expected returns, declining by around 2 percentiles by non-college and 4 percentiles by college graduates. The increase in expected earnings across occupations makes lower-return options more attractive, due to their higher marginal utility of earnings and lower utility costs. Conversely, risk-averse workers, now facing reduced income risks, move toward higher-return occupations. Consequently, in the non-college group, risk-tolerant workers' earnings rise by 1 percent, while risk-averse workers see a 5 percent increase, narrowing the gap from 14 to 10 log points. In the college sample, the gap decreases by 5 log points as risk-tolerant workers' earnings decline by 3 percent and risk-averse workers' rise by 2 percent. Despite these gains in equality, the policy slightly reduces total output by 0.2 and 0.6 percent, as workers shift to less profitable roles.

This paper contributes to the literature on the effect of risk aversion on labor market decisions. Previous research has examined whether risk aversion influences choices such as schooling (Belzil and Leonardi, 2007, 2013; Brodaty et al., 2014), college major selection (Paola and Gioia, 2012; Patnaik et al., 2022), and migration (Jaeger et al., 2010; Bauernschuster et al., 2014). A smaller body of work also documents the correlation between risk aversion and occupation choices (King, 1974; Bonin et al., 2007; Ahn, 2010; Buurman et al., 2012; Fouarge et al., 2014; Dillon, 2018). My paper is the first to account for the potential interaction between risk aversion and unobserved human capital in identifying the effect of risk aversion on occupation choices. Given that human capital is a core component driving self-selection into occupations and earnings disparities, it is essential to control for the correlation between risk aversion and human capital. Furthermore, the effects of risk aversion become amplified when human capital diverges across different careers. The model presented in this paper accommodates both the correlation between risk aversion and unobserved initial characteristics and the divergence of unobserved skills resulting from risk aversion in occupation choices.

Moreover, this paper is closely related to the literature that examines the drivers of differences in occupation choices and the resulting earnings disparities. Human capital—whether observed or unobserved, general or specific—has been identified as a major determinant of occupation choices (Keane and Wolpin, 1994; Pavan, 2011; Yamaguchi, 2012; Lindenlaub, 2017). Additionally, workers' beliefs about their abilities can vary and influence their labor market outcomes (Kinsler and Pavan, 2015; Bahk, 2020). Recently, Wiswall and Zafar (2018) provided suggestive evidence that individual preferences over non-pecuniary job attributes may impact career choices and lead to diverging earnings. This paper contributes to the literature by demonstrating that risk aversion heterogeneity serves as another dimension of occupational segregation and quantifying its effects on earnings dynamics.

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. Section 6 presents the results of the estimation and the decomposition analysis of the earnings gap across risk attitude groups. Section 7 provides the distributional impact of social insurance through risk aversion. Section 8 concludes.

2 National Longitudinal Survey of Youth 1997 (NLSY97)

The NLSY97 is an ongoing survey that initially included 8,984 individuals born between 1980 and 1984. They provide data on individual characteristics such as gender, race, education, and aptitude test (AFQT) scores. The dataset is especially well-suited for the analysis on occupation choices due to its detailed information on careers, including occupation codes, wages, and working hours. 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, 3,083 individuals whose job lottery choices, the AFQT score, and the education information are missing are removed from the sample. Next, I drop 115 individuals who ever participated in military services. I define a long-term transition to the labor market as working full-time (more than 30 hours per week) for at least three consecutive years. 795 individuals are dropped from the sample who never made long-term transitions into the labor market. 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 4,968 individuals with 50,760 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.

The hypothetical gamble choice is a valid measure of individual risk preferences. Previous studies show that the same gamble choice is strongly correlated with actual risky decisions such as asset allocations and self-employment (Kimball et al., 2008; Ahn, 2010). Moreover, the literature on risk preference measurement presents that survey measure of risk attitudes is a strong predictor of experiment and actual behaviors (Dohmen et al., 2011). Therefore, I use individual responses to hypothetical lottery questions to characterize their risk preferences.

It is also noteworthy that hypothetical gamble responses, collected in the middle of individual careers, may have been influenced by their wealth and labor market experiences before or at the moment of the survey. For example, under the assumption of decreasing relative risk aversion, those who happen to earn more become less risk-averse, which implies the reverse relationship between risk attitudes and earnings. Although the conclusion about the stability of individual risk preference is still mixed in the literature, I assume relative risk aversion remains constant within individuals, relying on previous studies showing that the attitudes elicited through the same job lottery choices remain stable against the change in earnings and employment status.[3]

[3]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

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. This classification ensures fine level of occupations with enough number of observations for the analysis. The final classification includes 81 occupations.[4]

Considering the focus of this paper is on the role of risk aversion, I assume that occupations can be broadly characterized by expected return and earnings stability: with all else equal, workers would choose high-return occupations, and risk-averse workers would prefer occupations that provide stable earnings streams within the spell.[5]

I first define the measure of earnings returns, Return_j, using residuals of log earning regression as follows:

$$\ln \mathrm{Earnings}_{ijt} = \alpha_i + \lambda_t + x_{it}'\beta + \upsilon_{\mathrm{r},ijt} \tag{1}$$

where $\mathrm{Earnings}_{ijt}$ represents the earnings of individual i with occupation j at period t. α_i refers to individual fixed effects, λ_t is period fixed effects, and x_{it} includes the cubic profiles of (potential) labor market experience. This allows to capture the variation of earnings across occupations controlling for self-selection on time-invariant individual characteristics; for example, professional occupations like lawyers exhibit higher earnings because high-ability workers self-select into them as well as those occupations provide higher general returns. Then, expected re-

preference changes over time, the changes in income and wealth are not the driver of the change in their risk attitudes.

[4]See Table B2 for the crosswalk and the full list of 81 occupations.

[5]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.

turn from each occupation is defined as the average of residual earnings within occupations, i.e. $\text{Return}_j = \hat{E}[\hat{\upsilon}_{\mathrm{r},ij't}|j' = j]$ where $\hat{E}[\cdot|j]$ represents the sample mean of observations conditional on occupation j.

To construct the measure of earnings stability, I replace α_i in (1) with individual-occupation fixed effects (α_{ij}) and extract residual earnings. Conditional on individual-occupation fixed effects, residuals ($\upsilon_{\mathrm{s},ijt}$) represent the variation of earnings within individual-occupation spells. This proxies unexpected shocks while excluding the cross-sectional variation including unobservable characteristics such as match quality. I define the mean of squared residual earnings within each occupation as a measure of occupation-specific earnings risks. In other words, $\text{Stability}_j = -\hat{E}[\hat{\upsilon}^2_{\mathrm{s},ij't}|j' = j]$. Finally, I transform both measures into percentile scores weighted by the number of observations in the whole sample of the NLSY97.[6]

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 of Black, women, less educated, and those with lower AFQT scores. The significant correlation between risk attitudes and observable characteristics have two implications. On the one hand, a simple comparison of labor market outcomes between risk attitude groups may not represent the effect of risk aversion. Therefore, I control for observable characteristics both in descriptive analysis in the next section and in the model of occupation choice in Section 4. On the other hand, provided that risk aversion significantly affects earnings, the effect of risk aversion may explain the differences in earnings between observed worker groups such as gender and race. That said, more risk-averse workers tend to have lower hourly rates of earnings and work slightly less weeks per year, higher earnings stability and lower expected returns.

[6]In Table B3, I implemented adaptive Lasso regression to explore the relationship between two measures with O*NET items. The stability is closely aligned with communicating with coworkers, less creative thinking, and the degree of automation. On the other hand, expected return is correlated with the level of competition, less time of walking or running, wearing protective equipment, and information analysis.

3 Descriptive Facts on Risk Aversion and Labor Market Outcome

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 return even conditional on covariates. Finally, the evidence reveals that selecting lower-return 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

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

where y_i is the dependent variable, the logarithm of lifetime average earnings and standard deviation of log 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 α_g which measures the average difference in the dependent variable relative to the most averse group. X_i is a vector of constant and 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 α_g for each specification for lifetime average earnings. Column (1) shows the unconditional earnings gap between risk attitude groups. More risk tolerant workers have significantly higher earnings. In particular, the most tolerant workers have around 22 percent higher earnings than the most averse workers. In column (2), I control for baseline observed characteristics. Although the gap in earnings declines, it still remains statistically and economically significant; the most tolerant workers have around 11 percent higher than the most averse workers. Risk aversion may also be correlated with family income and other non-cognitive personal traits such as responsibility and social skills. I examine whether those characteristics are the major driver of the earnings gap across risk attitude groups by controlling them. In column (3), I control for family income in 1997, as a proxy of individual family backgrounds, and measures of social skills and non-cognitive personal traits using Goldberg's Big Five personal factor survey (Deming, 2017). The earnings difference between groups is even larger conditional on additional characteristics. In column (4), I use the same sample to estimate the specification as in column (2) for comparison. The results suggest that the change in the coefficient estimates comes from the change in the sample.

In Table 3, I provide the results on the relationship between risk aversion and earnings volatility over lifetime. The results in column (1) suggest that more risk tolerant workers experience larger volatility of earnings over their careers. In column (2), the results remain the same conditional on observed characteristics. For example, the most tolerant workers have around 14 percent larger variance of earnings within their lives. The rest of the column confirms the relationship even with additional characteristics controlled.

I next investigate the relationship between risk aversion and earnings growth. In Figure 1, I plotted earnings growth profile relative to the first period for each risk attitude group. More risk-averse workers have flatter profiles of earnings growth relative to more risk-tolerant ones. For example, from the first period to 14 years of experience, the most tolerant have about 18 percentage points larger growth of earnings than the most averse. To control for the effect of observed characteristics on earnings growth, I estimate experience-earnings profiles by risk attitude groups using the following regression model:

$$\ln \mathrm{Earnings}_{it} = \sum_{g=1}^{3} \alpha_g \mathbf{1}(G_i = g) + \sum_{g=1}^{3}\sum_{s=1}^{T} \gamma_{gs}\mathbf{1}(G_i = g)\mathbf{1}(\tau(i,t) = s) + X_i'\beta + \phi_t + \psi_{\tau(i,t)} + \epsilon_{it} \quad (3)$$

where $\mathrm{Earnings}_{it}$ is the hourly earnings of individual i at period t. $\tau(i,t)$ represents the experience level of i at 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_{gs}, the excess earnings growth of group g from experience level 1 to s relative to the most averse workers.

Figure 2 confirms slower growth earnings for risk-averse workers. In particular, the gap in earnings growth between two extreme groups remains the same as around 18 percentage points. This implies that there exist dynamic components of risk aversion effects contributing to the earnings gap between risk attitude groups on top of contemporaneous premiums for taking risks.

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:

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

where y_{it} is the dependent variable (Stability_{it} and Return_{it}) 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. α_g indicates that workers of group g have α_g percentile higher stability and return compared to the most averse workers.

The findings in the first column of Table 4 support the idea of aversion to earnings risks, as more risk-averse workers tend to select occupations with higher earnings stability. For example, the most tolerant workers on average choose occupations with about 5 percentile lower earnings stability. In the subsequent two columns, the positive relationship between risk aversion and stability remains significant conditional on observed characteristics. In column (4) to (6), I present that risk-averse workers also choose lower-return occupations. On average, the most tolerant workers have around 7 percentile higher earnings return. Although the magnitude of the effect reduces by more than half, the difference remains significant when we control the observed worker characteristics. The results imply that workers are likely to choose different types of occupations based on their risk aversion and occupational characteristics.

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 B4, 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 first columns in Table 2 and Table 3 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 whole history of one's career path could matter.

3.3 Occupational Choice and Earnings Growth

Lastly, I explore the implication of risk aversion in occupation choices on earnings growth. The literature on human capital emphasizes the specificity of human capital to careers and the varying return to skills across occupations (see, for example, Keane and Wolpin, 1997; Pavan, 2011; Yamaguchi, 2012). This idea is particularly pertinent in this paper's context. If high-return occupations provide the opportunity to learn more valued skills, workers from those careers may accumulate human capital 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:

$$\ln \text{Earnings}_{it} = \beta_r \text{Return}_{it-1} + \beta_s \text{Stability}_{it-1} + \alpha_i + \psi_{j(i,t)} + \lambda_t + \epsilon_{it} \tag{5}$$

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 5 indicates that the return to experience in more profitable occupations is positive and significant; having worked in occupations with an 10 percentile higher profitability last period implies around 0.7 percent higher earnings today. Conversely, having worked in stable occupations last period shows smaller and insignificant return for current period. Consequently, if a worker starts their careers in stable occupations, they are more prone to have slower growth of earnings.

3.4 Summary of Descriptive Facts

In summary, the descriptive analysis suggests the existence of a significant relationship between risk aversion, earnings dynamics, and occupation choices. First, more risk-averse workers earn significantly lower and experience slower growth of earnings over their careers. I also document they have differential occupation choice patters to have higher earnings stability and lower returns. Choosing low-return occupations also predicts lower earnings in the future. These imply occupational segregation across risk attitude groups may result in both lower and flatter earnings profiles for more risk-averse workers.

While the evidence is suggestive of the effect of risk aversion on earnings, the causal effect through occupational selection cannot be identified because risk aversion may interact with unobserved heterogeneity such as human capital. Initial human capital at the beginning of the career may be correlated with risk aversion. Pre-market choices like internship and part-time jobs may be affected by risk aversion, resulting in heterogeneity in initial skill endowments. Moreover, human capital may grow at different rates across different occupations. Then, after sorting into different path of careers, risk-averse workers may experience slower growth of earnings because of diverging human capital. This indicates that the effect of risk aversion depends on the whole history of occupations. To distinguish various components related to risk aversion effeccts, in the next section, I develop a dynamic occupation choice model with risk aversion heterogeneity and individual- and occupation-specific human capital formation.

4 Occupation Choice Model with Risk Preference Heterogeneity

In this section, I present a dynamic model of occupation choice. The model is built upon the task-based approach suggested by Yamaguchi (2012) in three aspects: workers have different skills and their growth, each occupation is fully characterized by a vector of occupation characteristics, and workers also obtain non-pecuniary value from choosing occupations.[7] The main novelty of the model is the introduction of heterogeneous risk aversion. Risk aversion is correlated with initial skill endowments. It affects occupation choices because different occupations have different distribution of shocks. Finally, it may have dynamic impacts on earnings because different occupations also have different rates of skill accumulation.

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 returns and stability, $y_j = (y_{j1}, y_{j2})$. 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, they repeat this process infinitely.

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.

[7] Yamaguchi (2012) assumes that individuals choose a vector of continuous 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 of the utility over earnings is essential in incorporating the concept of risk aversion heterogeneity. For tractability, I assume workers choose occupations from a discrete choice set. I further assume unidimensional skill to focus on the impact of risk aversion.

For estimation, $\pi(y_j)$ and $q(y_j, s_t)$ are parameterized as

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

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 observed characteristics, and d_3 is a L dimensional vector which refers to learning heterogeneity across workers.

Initial skill endowments are defined as a function of worker characteristics including risk aversion.

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

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, higher return 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 dependent on their skills: if an individual is highly skilled, it may be easier for them to perform high-return tasks. 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. The moving cost captures search friction that workers in certain occupations may receive offers only from similar professions. It also implicitly contains the occupational specificity of human capital; workers may accumulate skills only valuable in similar occupations.

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

$$\ln w(j; s_t, e) = \pi_0 + \pi_1' y_j + q_0 s_t + q_1 y_j s_t + e(y_j, e)$$

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

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 is that risk-averse workers prefer occupations with lower variances of shocks $(e(y, e), \eta(y, \eta))$. Since different occupations offer different output prices and returns to skills, differential occupation choices instantaneously affect earnings. The selection behavior on risk aversion also has an indirect impact on future outcomes because skill accumulation depends on occupation choices. In particular, if $d_{2,\text{stability}} < d_{2,\text{return}}$, skills are accumulated faster in the high-return careers and thus occupation choices and earnings of risk-averse workers may further diverge from those of the risk-tolerant.

5 Estimation

I estimate the model parameters using non-college and college sample separately from 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 aversion 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.

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. It is noteworthy that I assume expected earnings are solely determined by occupation choices and skills. In other words, I cannot separately identify the potential earnings discrimination over observed characteristics from unobserved initial skills.

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 the 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 Risk Aversion Types

Risk aversion is heterogeneous across individuals through varying γ in their utility over earnings. I assume that workers in the same lottery choice group have the same coefficient of relative risk aversion. I estimate these coefficients outside of the model based on Kimball et al. (2008, 2009) who use the same hypothetical lottery choices in other surveys to measure the individual relative risk aversion. Under CRRA utility assumption, hypothetical gamble choice can be represented as inequality conditions with respect to risk aversion or risk tolerance. Kimball et al. (2008) assume the log-normal distribution of relative risk aversion which also involves measurement error in lottery choices. The distribution of coefficients and the measurement error can be estimated using gamble choices and the Maximum Likelihood Estimation. However, the distribution of the error is only identified when the gamble choices available multiple times for the same individual. Lack of panel structure, Kimball et al. (2009) takes the variance estimate of risk aversion coefficients from Kimball et al. (2008) and estimate the mean of coefficients and the variance of the measurement error. I follow the same procedure to estimate the distribution of risk aversion coefficients and measurement errors. Then, I calculate the conditional expected value of coefficients for each group. Details about the risk aversion estimation is provided in Subsection A.1.

[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.

5.3 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. 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).

Optimal Policy 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

$$v_j(s_{it}, \gamma_i, x_i, j_{i,t-1}) = U_j(s_{it}, \gamma_i, x_i, j_{i,t-1}) + \beta \int \overline{V}(s', \gamma_i, x_i, j)\psi(s'|x_i, s_{it}, j)ds' \tag{16}$$

where $\overline{V}(\cdot) = E_\epsilon[V(\epsilon_t, \cdot)]$. With Type 1 Extreme Value distribution of preference shock, $\overline{V}(s, \gamma_i, x_i, j)$ has a closed-form expression:

$$\overline{V}(s_{it}, \gamma_i, x_i, j_{i,t-1}) = C_{\text{euler}} + \ln\left(\sum_j \exp\left(v_j(s_{it}, \gamma_i, x_i, j_{i,t-1})\right)\right) \tag{17}$$

where C_{euler} represents Euler's constant. Substituting $\overline{V}(\cdot)$ in (16) and replacing $v_j(\cdot)$ in (17), we have the bellman equation. Given $\overline{V}^*(\cdot)$, the fixed point of the bellman equation, $v_j^*(\cdot)$ is calculated by replacing $\overline{V}$ with $\overline{V}^*$ in (16). Then, the conditional choice probability of occupation j becomes

$$P(j|s_{it}, \gamma_i, x_i, j_{i,t-1}) = \frac{\exp(v_j(s_{it}, \gamma_i, x_i, j_{i,t-1}))}{\sum_{j'} \exp(v_{j'}(s_{it}, \gamma_i, x_i, j_{i,t-1}))} \tag{18}$$

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

$$l_1(z_{i1}|s_1, \gamma_i, x_i; \theta) = P_1(j_{i1}|s_1, \gamma_i, x_i; \theta)\phi(w_{i1}|s_1, j_{i1}; \theta) \tag{19}$$

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

$$
\begin{aligned}
E[w_{i1}|s_1, j_{i1}] &= \pi_0 + \pi_1' y(j_{i1}) + (q_0 + Q_1 s_1)' y(j_{i1}) \\
V[w_{i1}|s_1, j_{i1}] &= \sigma^2(y(j_{i1})).
\end{aligned} \tag{20}
$$

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

$$
l(z_{it}|s_t, \gamma_i, x_i, j_{i,t-1}; \theta) = P(j_{it}|s_t, \gamma_i, x_i, j_{i,t-1}; \theta)\phi(w_{it}|s_t, j_{it}; \theta). \tag{21}
$$

Subsuming θ, the likelihood of an individual's labor market profile is

$$
\begin{aligned}
l^*(Z_i|\gamma_i, x_i) = \int_{s_1} \cdots \int_{s_T} \Big[& \psi_1(s_1|x_i) l_1(z_{i1}|s_1, \gamma_i, x_i) \\
& \prod_{\tau=2}^{T} \psi(s_\tau|s_{\tau-1}, x_i, j_{i,t-1}) l(z_{i\tau}|s_\tau, \gamma_i, x_i, j_{i,\tau-1}) \Big] ds_1 \cdots ds_T
\end{aligned} \tag{22}
$$

Finally, the maximum likelihood estimation problem can be defined as

$$
\hat{\theta} = \arg\max_{\theta} \sum_i \log l^*(Z_i|\gamma_i, x_i; \theta) \tag{23}
$$

5.4 Expectation-Maximization (EM) Algorithm

Directly estimating (23) is computationally costly since 1) the bellman equation should be solved every iteration, and 2) the individual log-likelihood has the integration (summation) of probabilities inside the logarithm due to unobserved heterogeneity, and thus all parameters must be estimated at the same time. To overcome these challenges, I implement the EM algorithm to estimate the model, following the method in Arcidiacono and Miller (2011). First, to circumvent the necessity of fully solving the model, I exploit CCP estimators, suggested by Hotz and Miller (1993), that utilize the relationship between value functions and the probabilities of choosing alternatives.

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 the posterior distribution of unobserved heterogeneity and estimates the parameter with the Maximum Likelihood Estimation given the updated CCP's. This approach reintroduces additive separability of the log-likelihood, which considerably reduces the computation time. 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.

The basic idea of the estimation algorithm is as follows: in the expectation stage, the conditional probability of each individual's being in each unobserved state at each period is calculated by Bayes' rule given their observations and current parameter estimates. Given the estimated CCP's and parameter estimates, the CCP's can be updated following Hotz and Miller (1993). In the maximization stage, with the conditional distribution of unobserved state and the CCP's given, the log-likelihood of labor market profiles can be constructed treating the unobserved state as if it is observed with the posterior distribution as weights. The further details of the algorithm are provided in Appendix A.

The estimation calls for additional restrictions to proceed. First, for computational stability, earnings for utility function are rescaled to unit variance and earnings utility is relocated so that workers have zero utility when hourly earnings rate is 1 dollar. Next, I restrict the sample to the most and the least risk-tolerant workers for simplicity. Finally, I estimate the model with non-college 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. More detailed procedures are provided in Subsection A.5.

6 Estimation Results

I present the estimation results for the non-college and college sample respectively. First, I discuss the parameter estimates and the model fit. Then, I decompose the earnings gap between the most and the least risk-tolerant workers.

6.1 Estimates and Model Fit

I report the parameter estimates in Table 6, Table 7, and Table 8. Notably, there is significant variation in the standard deviation of shocks across occupations. For transitory shocks, the standard deviation ranges from 0.1 to 0.4 in the non-college sample and up to 0.36 in the college sample. The measure of earnings stability is particularly strongly related to transitory risks: a 10-percentile increase in stability corresponds to a decrease in transitory risks by 0.03 and 0.02 for the non-college and college samples, respectively. A similar increase in occupational return results in a more modest decrease in transitory risks of approximately 0.01. The standard deviation of persistent risks, scaled by the average skill price (0.33), ranges from 0.1 (0.12) to 0.15 (0.16) in the non-college (college) sample. While variation in persistent risks across occupations is less pronounced than for transitory risks, it rises with occupational return and declines with earnings stability.

Furthermore, the rate of human capital accumulation varies significantly across occupations. For non-college graduates, the parameter estimate for the occupation-specific accumulation rate (d_2) is $(0.19, 0.12)$, with both values statistically and economically significant. For example, given the average skill price, workers in occupations with a 10-percentile higher return in the previous period experience approximately a 0.63 percent $(0.33 \times 0.19 \times 0.1)$ earnings growth. Those in occupations with 10-percentile higher stability experience a 0.4 percent increase in earnings. The effect is even larger among college graduates: a 10-percentile higher occupational return implies a 1 percent increase in earnings, while stability's impact is negligible. These results suggest that high-return occupations are associated with faster human capital accumulation, indicating that risk-averse workers in safer careers may face slower earnings growth compared to those in higher-return, riskier careers.

Finally, risk aversion has a significant negative association with initial skill. Among non-college graduates, the most risk-averse workers have approximately 0.25 standard deviations lower skills than the most risk-tolerant workers—a difference larger than the skill gap between Black and non-Black workers, which amounts to 0.16 standard deviations. This skill difference translates into an approximately 8.3 percent initial earnings gap. Among college graduates, the difference in initial skills between the most and least risk-tolerant workers is 0.42 standard deviations, amounting to about 16 percent higher initial earnings for the least risk-averse workers. This significant association between risk aversion and unobserved initial skills highlights the importance of accounting for unobserved heterogeneity when estimating the effects of risk aversion on earnings through occupational selection.

Overall, the model closely replicates the observed data patterns. I simulate each individual 100 times over their careers and calculate the predicted paths of average earnings and occupational characteristics. Figure 3 and Figure 4 compare the observed and predicted profiles of earnings and occupational characteristics. For the non-college sample, the predictions align closely with observed data patterns. For college graduates, the model accurately predicts occupation choices, while earnings predictions match observed trends until the sixth year of experience, after which the model overpredicts earnings. This overprediction likely arises because the model does not incorporate age-related components in earnings and skill accumulation; in other words, the rate of skill accumulation remains constant across age. While incorporating aging effects or treating the model as a finite-horizon problem could address these issues, doing so would significantly increase computational demands.

In Figure 5 and Figure 6, I present the average earnings and occupational attributes by levels of risk aversion. The predicted earnings closely match actual levels in the non-college sample. For the most risk-tolerant workers, the model slightly overpredicts both expected returns and earnings stability, yet it captures the trend that more risk-averse workers select occupations with lower returns and greater stability. Among college graduates, predicted earnings for risk-tolerant workers exceed actual earnings, with slight overpredictions in expected returns and underpredictions in earnings stability. Nonetheless, these discrepancies are minor, and the model's predictions for risk-averse workers' labor market profiles align well with the observed data.

6.2 Decomposition of Risk Aversion Effect on Earnings

The observed earnings gap between the most and least risk-averse workers can be attributed to several factors: initial skill heterogeneity, lower returns for safer occupations, and differential human capital accumulation. As suggested by the parameter estimates, risk preferences are significantly correlated with initial skill endowments. Differences in initial skills contribute to earnings inequality both through higher returns to skills and through self-selection into high-return occupations. Workers with higher initial skills earn more within the same occupation due to skill returns and are also more likely to select high-return occupations, further widening the gap. This initial advantage compounds over time, as skill accumulation is faster both for workers with higher initial skills and in high-return occupations.

Secondly, risk-averse individuals tend to select into lower-return occupations, which translates into lower immediate returns because both the output price and returns to skills are higher in high-return occupations. Lastly, the impact of this occupational choice on lifetime earnings is amplified by differences in human capital accumulation across careers.

To quantify the contribution of each channel to the earnings gap between the two extreme risk-attitude groups, I use the estimated model to perform a decomposition analysis in three steps. First, I replicate the observed earnings gap between the two groups by simulating earnings and occupation choice profiles for each individual in the sample 100 times. Then, to isolate the impact of occupation choice from that of initial heterogeneity, I fix occupation choices and simulate earnings profiles under the assumption that there is no heterogeneity in demographic characteristics, initial skills, or initial job preferences. Next, I remove occupation-specific differences in returns to skills and skill accumulation to isolate the effect of human capital accumulation from the immediate premium associated with riskier occupations. Specifically, I fix skill prices ($q_0 + Q_1'y$) and the rate of learning-by-doing ($d_2'y$) at the average levels of the baseline sample.[9] Using these simulated datasets, I compare average log lifetime earnings between the most and least risk-tolerant workers.

The decomposition results are presented in Table 9. In the first column, I replicate the earnings gap using the observed sample that is used in model estimation. On average, the most risk-tolerant workers exhibit approximately 14.3 log points higher lifetime earnings compared to the most risk-averse workers. The baseline model predicts a similar gap of 14 log points. In the third column, where both observed and unobserved initial heterogeneity are controlled, the gap decreases by approximately 9.8 log points, indicating that around 70 percent of the earnings gap is due to the correlation between risk aversion and initial heterogeneity. The remaining 30 percent (4.2 log points) can be attributed to the differential occupational choices made by risk-averse workers. In column (4), I show that occupational differences in instantaneous returns account for about a 2.3 log point gap, explaining 16 percent of the total baseline gap. The remaining 1.9 log points reflect the effect of slower human capital growth for risk-averse workers.

For college graduates, the model overpredicts the earnings gap: while the observed gap is 17.6 log points, the baseline model estimates it at 23.5 log points. Of this predicted gap, initial heterogeneity accounts for 15.8 log points, or 67 percent. The remaining 33 percent reflects the influence of occupational choice differences, with nearly 48 percent of this occupational effect explained by diverging rates of human capital accumulation over time between risk-tolerant and risk-averse workers.

In summary, the decomposition analysis shows that a significant portion of the earnings disparity between the most and least risk-tolerant workers is driven by differences in occupational

[9] The reason for removing occupation-specific returns to skills is as follows: if two workers have identical skill trajectories, the worker in a higher skill-price occupation will have a steeper earnings profile, due to higher returns. Given that human capital here is defined as the market value of skills, this creates an additional channel for human capital growth.

choice, independent of initial heterogeneity. Moreover, the effects of occupation choice differences are significantly magnified by differences in human capital accumulation. This suggests that examining risk aversion's impact on earnings solely through immediate compensation for risk may underestimate the broader influence of occupational choices on lifetime earnings.

7 Distributional Impact of Social Insurance

In this section, I employ the estimated model to analyze the distributional effects of a policy providing an earnings floor for workers. Social insurance programs, such as Social Security and Guaranteed Minimum Income, are designed to prevent earnings from falling below a certain threshold, protecting workers from adverse earnings shocks and reducing income inequality. These policies can affect labor market allocations in two primary ways. First, by limiting negative earnings shocks, the earnings floor raises expected earnings across occupations. With CRRA utility, marginal utility is greater for lower-return occupations, making these occupations relatively more attractive under the earnings floor. Additionally, high-return occupations entail higher utility costs at a given expected earnings level. Thus, an increase in expected earnings across occupations can incentivize workers toward lower-return options. Second, the earnings floor reduces the variance in earnings shocks, allowing risk-averse workers to consider higher-return, less stable occupations they might avoid without this safety net.

For this analysis, I set the earnings floor at \$9.3, representing 60 percent of the median earnings in the data. This threshold corresponds to the poverty definition used in several countries, including the United Kingdom and the European Union.[10] I simulate labor market profiles for each individual in the sample 100 times, applying the earnings floor.

Table 10 presents the occupational allocations for the non-college sample under the earnings floor policy. On average, workers select occupations with slightly lower returns (a decrease of 0.3 percentiles). This trend is more pronounced among risk-tolerant workers, whose expected

[10] For example, See the EU's at-risk-of-poverty threshold definition: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:At-risk-of-poverty_rate

return decreases by 3.2 percentiles. This is likely due to the increased expected earnings, which disincentivizes high-return occupations. Conversely, risk-averse workers select occupations with marginally higher returns (an increase of 0.3 percentiles). By reducing earnings risk, the earnings floor enables risk-averse workers to consider high-return occupations they would otherwise avoid. Although both groups experience disincentives to pursue high-return occupations, the reduced risk allows risk-averse workers to maintain or even increase their occupational returns relative to risk-tolerant workers. Changes in earnings stability are less marked but show similar trends: risk-tolerant workers shift toward higher-stability occupations, while risk-averse workers experience a slight reduction in stability.

In Table 11, I present lifetime average earnings by risk-attitude group and total output under each scenario. Under the earnings floor, average lifetime earnings increase by around 5 percent. Risk-averse workers see a 5 percent rise in earnings, while risk-tolerant workers experience a more modest 1 percent increase. As a result, the earnings gap between the two groups narrows by 4 log points, or approximately 29 percent of the baseline gap.

Two main factors drive this differential impact of the earnings floor on risk-averse workers. First, following the policy's implementation, risk-averse workers shift toward relatively higher-return occupations, while risk-tolerant workers opt for lower-return choices. This occupational reallocation increases risk-averse workers' outputs while reducing those of risk-tolerant workers. To explore the effect of occupational adjustment, in the third column of Table 11, I fix occupation choices at their counterfactual levels (as if the floor were present) and calculate lifetime earnings without the earnings floor. Comparing these earnings to the baseline shows the change in individual productivity due to occupational reallocation. Results indicate that risk-tolerant workers experience a 2 percent decrease in average output, while risk-averse workers see a small productivity gain. Consequently, the gap in individual productivity narrows by 2 log points, accounting for half of the earnings gap reduction under the policy.

Second, because risk-averse workers are, on average, less skilled, their earnings are more likely to fall below the floor, allowing them to benefit more from the earnings floor than risk-tolerant workers. When holding occupation choices constant under the earnings floor, earnings rise by 4 log points for risk-tolerant workers and 5 log points for risk-averse workers. This larger increase for risk-averse workers highlights that the earnings floor provides them with relatively greater direct support.

Table 12 and Table 13 report the results for college graduates. In response to the earnings floor, risk-tolerant workers transition to occupations with 4 percentiles lower expected returns and 3.1 percentiles higher stability, whereas risk-averse workers experience a 1-percentile increase in returns and a 0.7-percentile decrease in stability. The third column in Table 13, shows that individual outputs decline by 3 log points for risk-tolerant workers and increase by 1 log point for risk-averse workers, narrowing the productivity gap between the groups by 4 log points. While risk-tolerant workers do not benefit directly from the earnings floor, risk-averse workers gain an additional 1 log point in earnings. This smaller direct impact of the floor relative to non-college sample reflects the generally higher earnings of college graduates, who are less likely to fall below the threshold. Overall, the earnings gap is reduced by 5 log points, or 21 percent of the baseline gap, with 80 percent of this reduction attributable to productivity changes due to occupational reallocation.

In summary, the earnings floor reduces the earnings disparity between risk-averse and risk-tolerant workers by approximately 20–30 percent. More than half of this reduction results from occupational reallocation, with the remaining portion attributed to the larger earnings support provided to risk-averse workers. However, while social insurance can reduce earnings gaps, it also leads to a decrease in total output. Under the earnings floor, total output declines by approximately 0.2–0.6 percent, as workers, on average, choose less profitable occupations.

8 Conclusion

This paper studies how differences in risk aversion affect occupational choices and contribute to earnings disparities among workers. Using individual-level data on hypothetical gamble choices and detailed career histories, I first provide evidence of the relationship between risk aversion, occupation selection, and earnings inequality. By classifying workers into four groups based on their lottery choices, ranging from the most risk-tolerant to the most risk-averse, I show that more risk-tolerant workers tend to achieve significantly higher earnings and experience greater earnings growth over their life cycles. These individuals are more likely to choose occupations with higher returns but lower earnings stability, which, regardless of future occupation choices, also tend to predict faster earnings growth over time.

I develop and estimate a dynamic occupational choice model in which workers differ in both initial skills and risk preferences, making decisions among occupations that offer varying levels of risk, return, and opportunities for skill accumulation. Using the estimated model, I quantify the roles of initial heterogeneity, occupational selection, and differential human capital accumulation in shaping the effects of risk aversion on earnings. The results indicate that more than half of the observed effects can be attributed to risk-averse workers selecting different types of occupations. Moreover, the differential growth in human capital significantly contributes to the impact of occupational choices on earnings inequality.

The model also allows for an evaluation of the distributional impact of social insurance policies in the labor market. Specifically, providing an earnings floor influences occupational allocation by reducing economic risks, which enables risk-averse workers to pursue occupations with relatively higher returns. This reallocation substantially narrows the earnings inequality between the most and least risk-tolerant workers. Additionally, the policy directly affects the earnings distribution by providing greater support to risk-averse workers, who are typically less skilled and thus benefit more from a guaranteed minimum income.

The findings of this paper have important implications. First, the strong link between risk aversion and earnings suggests that a portion of the observed gaps in labor market outcomes across worker groups—such as those defined by gender and race—may stem from differences in risk preferences. Previous research has consistently shown a systematic relationship between risk aversion and these characteristics. Second, social insurance policies have the potential to mitigate earnings inequality by reshaping labor market allocations according to workers' risk preferences.

This study opens several avenues for future research. One potential extension is to incorporate the estimation of individual risk aversion coefficients directly into the model. Given that occupations differ in terms of earnings risks, they can be viewed as lotteries with varying risk-return profiles. This makes occupational choices a valuable source of variation for inferring individuals' real-life risk preferences. Another direction for future work is to include other types of economic risks, such as occupation-specific unemployment risk. For instance, this could be modeled by allowing working weeks per year to be stochastic, with their distribution varying across occupations and workers. Finally, the economic framework developed in this paper is sufficiently flexible to analyze other discrete choices in the labor market, including decisions related to marriage, labor supply, and job mobility.

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Figures and Tables

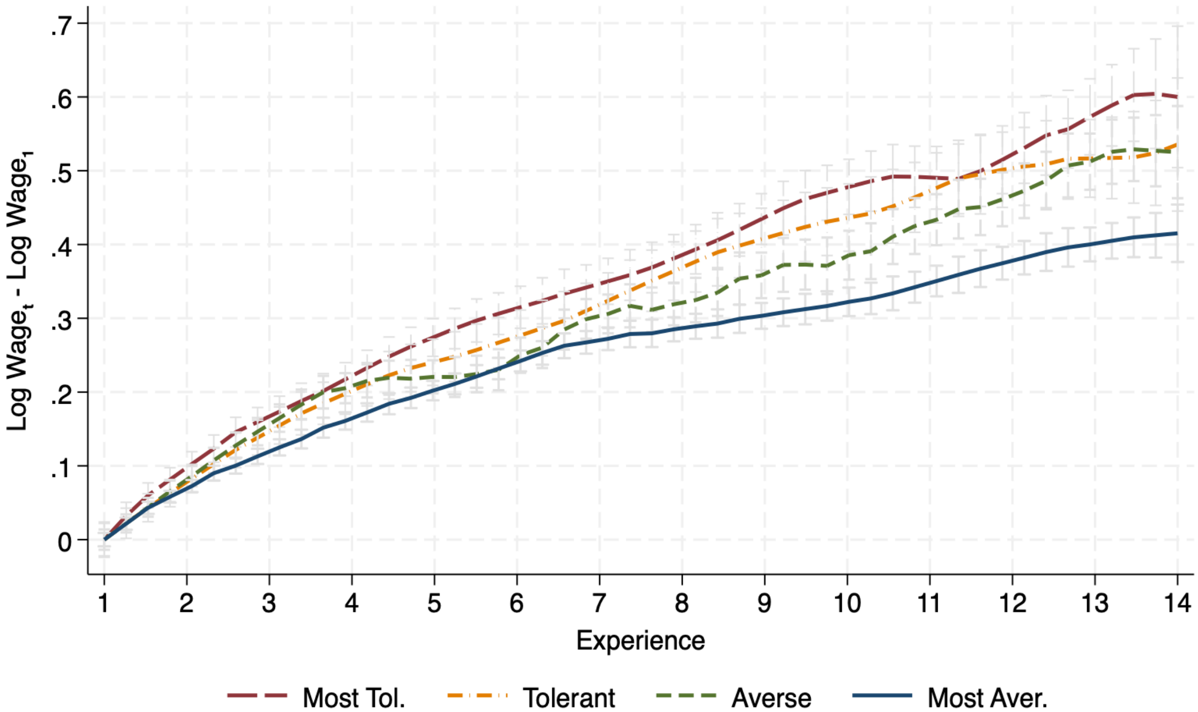


Figure 1: Risk Aversion and Earnings Growth

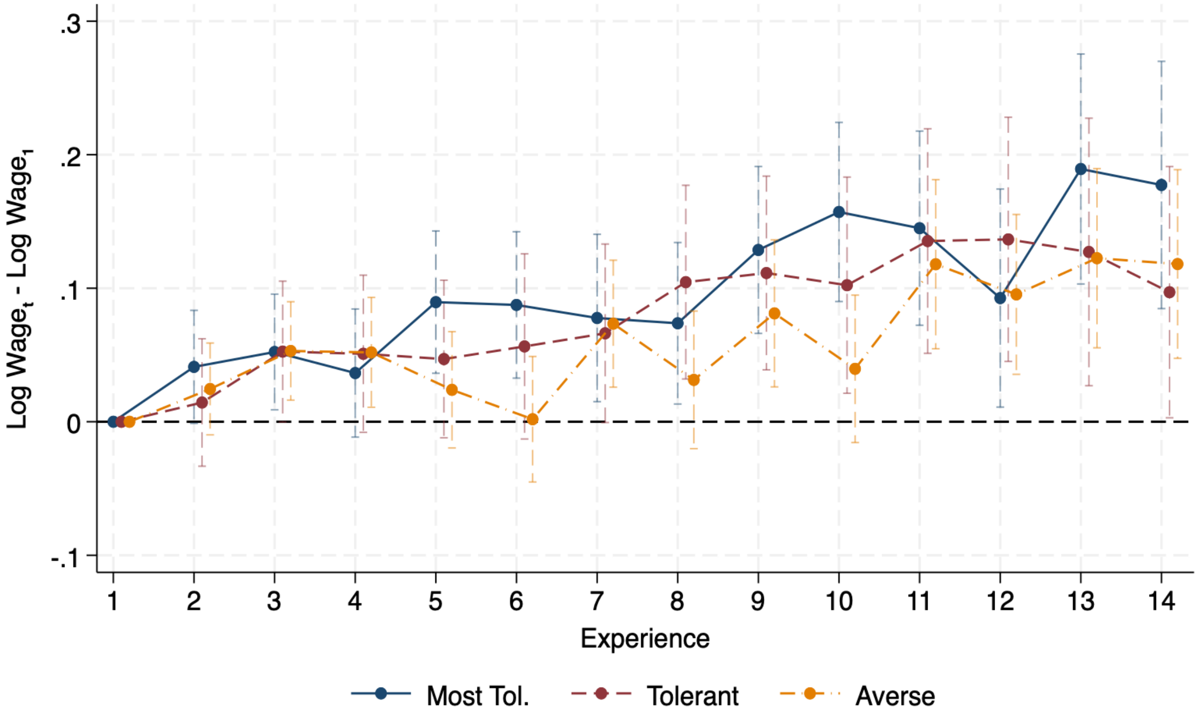
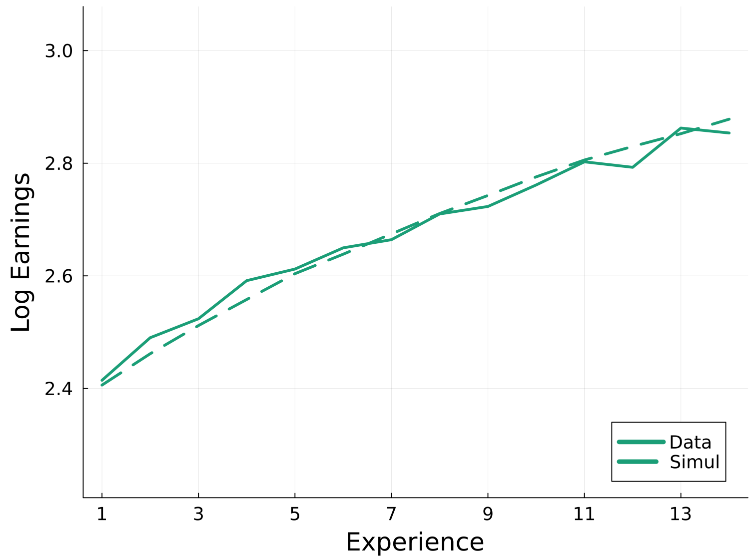


Figure 2: Risk Aversion and Relative Earnings Growth

(a) Log Earnings



(b) Occupational Characteristics

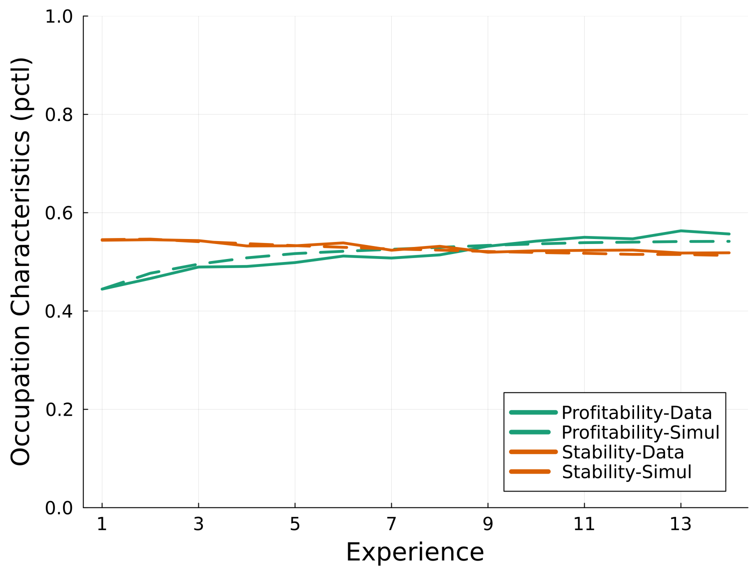
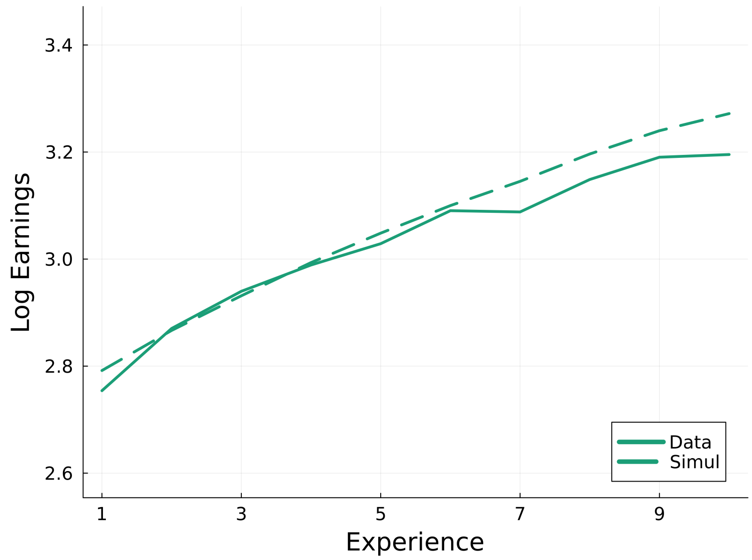


Figure 3: Model Fit - Non-college

(a) Log Earnings



(b) Occupational Characteristics

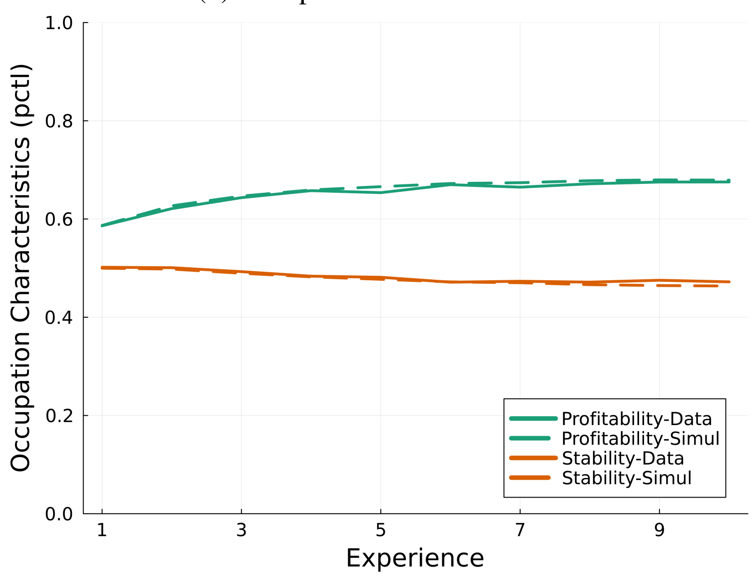


Figure 4: Model Fit - College

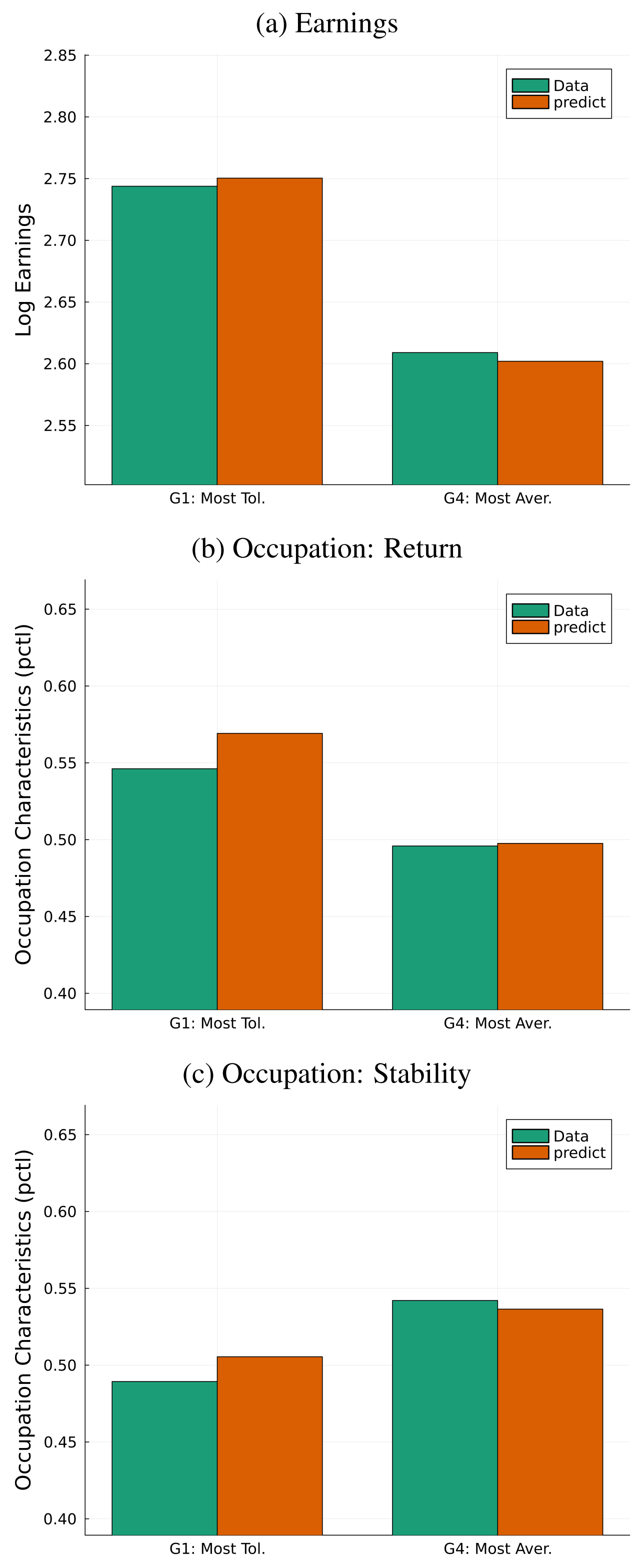


Figure 5: Model Fit by Risk Attitude Groups - Non-college

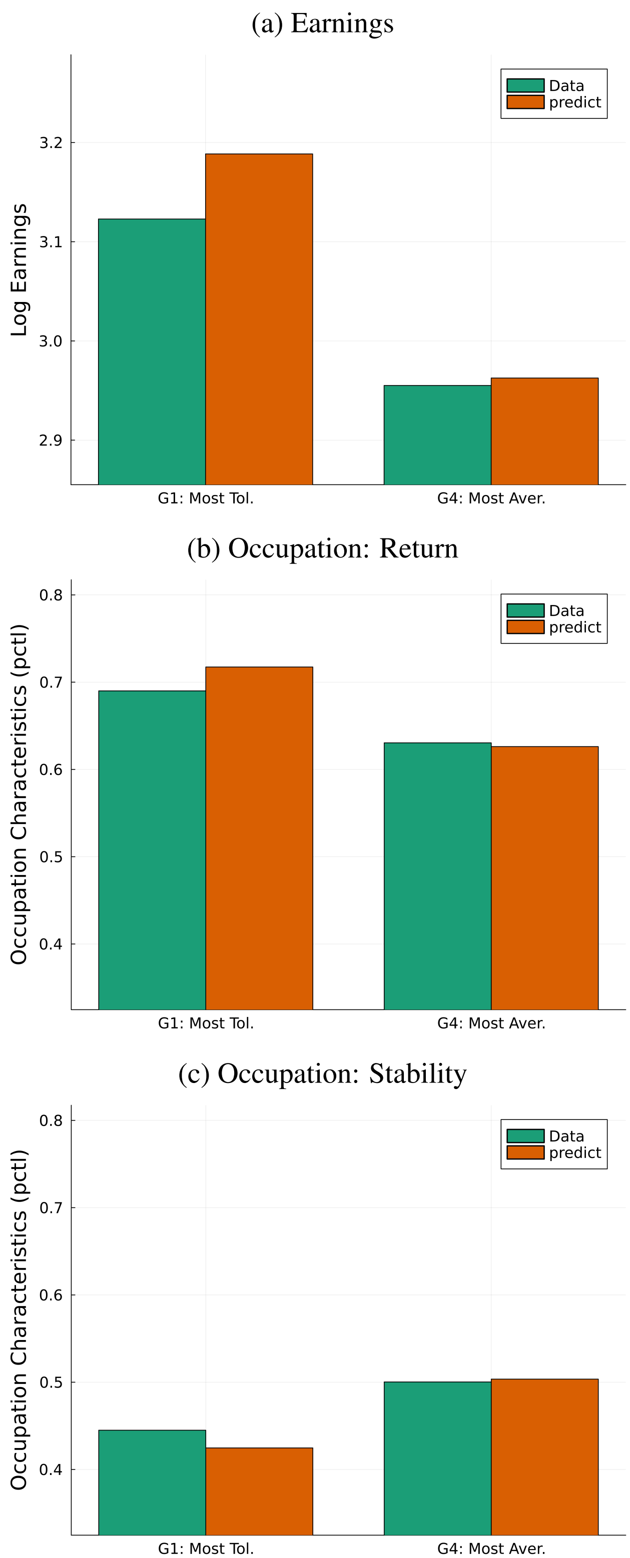
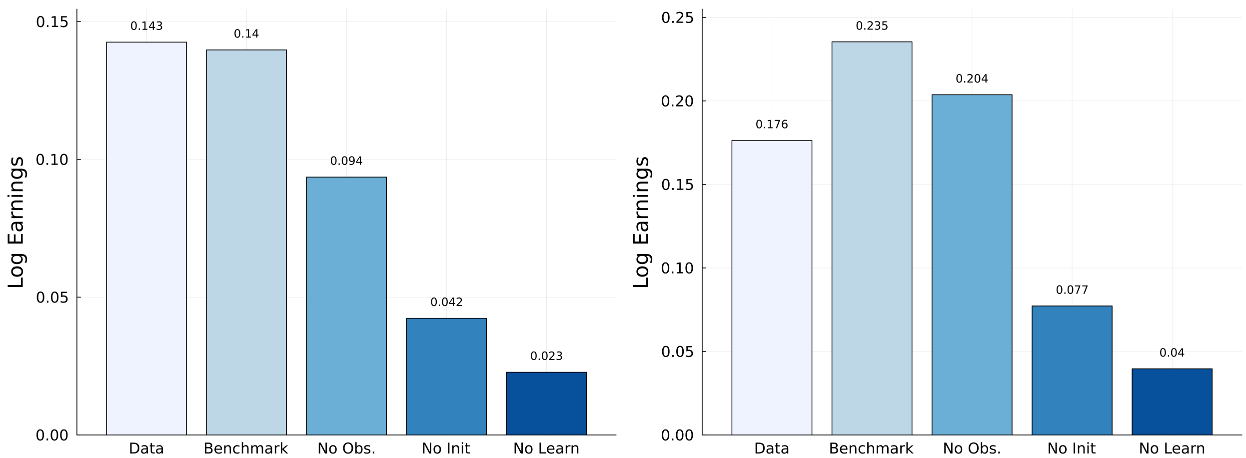


Figure 6: Model Fit by Risk Attitude Groups - College



(a) Non-college

(b) College

Figure 7: Decomposition of Earnings Gap between the Most and Least Risk-averse Workers

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}	721	556	1,085	2,544	4,906
N_{obs}	6,491	4,859	9,885	22,922	44,157
	Demographics				
Black	0.21	0.22	0.23	0.29	0.26
Hispanic	0.19	0.17	0.21	0.21	0.2
Men	0.63	0.56	0.52	0.47	0.51
Education	13.9	14.1	13.9	13.2	13.6
AFQT	0.2	0.28	0.16	-0.1	0.04
	Labor Market Outcomes				
Log Earnings (per hours)	2.91	2.89	2.83	2.72	2.79
Weeks Worked (per year)	45.7	45.8	45.6	44.6	45.1
Earnings Stability	0.48	0.49	0.5	0.53	0.51
Profitability	0.6	0.59	0.56	0.54	0.56

Source.–National Longitudinal Survey of Youth 1997.

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

	(1)	(2)	(3)	(4)
Most Tolerant	0.221***	0.110***	0.159***	0.159***
	(0.019)	(0.016)	(0.033)	(0.033)
Tolerant	0.186***	0.068***	0.092**	0.097**
	(0.021)	(0.018)	(0.039)	(0.039)
Averse	0.118***	0.030**	0.043	0.044
	(0.016)	(0.013)	(0.028)	(0.028)
Demographics		✓	✓	✓
Non-cognitive			✓	
Parent income 97			✓	
N	4,900	4,900	1,042	1,042
R^2	0.039	0.364	0.386	0.379

Source.–National Longitudinal Survey of Youth 1997

Notes.–The estimates are from the regression of lifetime average of earnings on risk attitude group indicators. Demographic variables in the second column include race, gender, age-adjusted AFQT scores and education level. The third and fourth columns restrict 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 Earnings Volatility (Base: Most Averse)

	(1)	(2)	(3)	(4)
Most Tolerant	0.194***	0.137***	0.148***	0.153***
	(0.029)	(0.029)	(0.057)	(0.058)
Tolerant	0.126***	0.080**	0.108*	0.112*
	(0.033)	(0.033)	(0.063)	(0.064)
Averse	0.117***	0.083***	0.087*	0.091*
	(0.025)	(0.025)	(0.050)	(0.050)
Demographics		✓	✓	✓
Non-cognitive			✓	
Parent income 97			✓	
N	4,878	4,878	1,041	1,041
R^2	0.011	0.040	0.096	0.086

Source.–National Longitudinal Survey of Youth 1997

Notes.–The estimates are from the regression of lifetime average of earnings on risk attitude group indicators. Demographic variables in the second column include race, gender, age-adjusted AFQT scores and education level. The third and fourth columns restrict 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 4: Risk Aversion and Occupation Choice

	Stability (pctl)			Return (pctl)		
	(1)	(2)	(3)	(4)	(5)	(6)
Most Tolerant	-0.052***	-0.035***	-0.048***	0.067***	0.026***	0.048***
	(0.008)	(0.008)	(0.015)	(0.008)	(0.007)	(0.014)
Tolerant	-0.034***	-0.022**	-0.000	0.051***	0.016*	0.022
	(0.009)	(0.009)	(0.019)	(0.009)	(0.009)	(0.017)
Averse	-0.024***	-0.016**	-0.029**	0.022***	-0.003	0.027*
	(0.007)	(0.007)	(0.014)	(0.007)	(0.007)	(0.014)
Demographics		✓	✓		✓	✓
Noncog			✓			✓
Parent Income at 97			✓			✓
N	48,253	48,253	10,739	48,253	48,253	10,739
R^2	0.012	0.040	0.054	0.054	0.151	0.179

Source.–National Longitudinal Survey of Youth 1997

Note.–The estimates are from the regression of earnings stability and return measures on risk attitude group indicators. Demographic variables in the second column include race, gender, age-adjusted AFQT scores and education level. The third column restrict 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. Standard errors clustered at individual-occupation level.

Table 5: Regression of Log Earnings on Last Occupation Attributes

Log Earnings, t	All	High School	College
Earnings Return (pctl), $t-1$	0.067***	0.071***	0.055**
	(0.013)	(0.016)	(0.022)
Earnings Stability (SD), $t-1$	0.010	0.016	0.001
	(0.011)	(0.013)	(0.020)
Current Occ FEs	✓	✓	✓
Indiv FEs & Year Fes	✓	✓	✓
Covariates	✓	✓	✓
N	39,019	24,086	14,930
R^2	0.702	0.623	0.723

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 6: Uncertainty and Wage Parameters

	Wage			Risk	
	Estimate	Standard Error		Estimate	Standard Error
	Non-college			*Non-college*	
π_0	2.203	0.017	a_0	0.43	0.008
$\pi_{1,\text{Return}}$	0.343	0.017	$a_{1,\text{Return}}$	-0.076	0.009
$\pi_{1,\text{Stable}}$	0.088	0.015	$a_{1,\text{Stable}}$	-0.282	0.008
q_0	0.311	0.015	c_0	0.353	0.044
$q_{1,\text{Return}}$	0.067	0.015	$c_{1,\text{Return}}$	0.116	0.039
$q_{1,\text{Stable}}$	-0.044	0.014	$c_{1,\text{Stable}}$	-0.067	0.042
	College			*College*	
π_0	2.481	0.026	a_0	0.393	0.014
$\pi_{1,\text{Return}}$	0.446	0.025	$a_{1,\text{Return}}$	-0.122	0.012
$\pi_{1,\text{Stable}}$	0.099	0.022	$a_{1,\text{Stable}}$	-0.203	0.013
q_0	0.43	0.023	c_0	0.421	0.045
$q_{1,\text{Return}}$	-0.018	0.022	$c_{1,\text{Return}}$	0.004	0.042
$q_{1,\text{Stable}}$	-0.063	0.018	$c_{1,\text{Stable}}$	-0.122	0.041

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 Parameters

	Skill			Initial Skill	
	Estimate	Standard Error		Estimate	Standard Error
	Non-college			*Non-college*	
d_0	-0.036	0.022	$H_{1,\text{Black}}$	-0.161	0.073
d_{11}	0.887	0.009	$H_{1,\text{Male}}$	0.462	0.063
d_{12}	0.018	0.003	$H_{1,\text{AFQT}}$	0.435	0.065
$d_{2,\text{Return}}$	0.191	0.025	$H_{1,\gamma}$	-0.049	0.018
$d_{2,\text{Stable}}$	0.123	0.021			
$d_{3,\text{Black}}$	-0.044	0.011			
$d_{3,\text{Male}}$	0.059	0.01			
$d_{3,\text{AFQT}}$	0.03	0.01			
	College			*College*	
d_0	-0.072	0.03	$H_{1,\text{Black}}$	-0.094	0.089
d_{11}	0.907	0.009	$H_{1,\text{Male}}$	0.009	0.077
d_{12}	0.011	0.004	$H_{1,\text{AFQT}}$	0.286	0.085
$d_{2,\text{Return}}$	0.307	0.03	$H_{1,\gamma}$	-0.088	0.017
$d_{2,\text{Stable}}$	0.005	0.026			
$d_{3,\text{Black}}$	-0.02	0.014			
$d_{3,\text{Male}}$	0.06	0.012			
$d_{3,\text{AFQT}}$	0.042	0.013			

Source.–National Longitudinal Survey of Youth 1997

Note.–The estimates are for skill transition and intiial skills. 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 $s_1 = h_0 + H_1(x', \gamma)' + \xi$.

Table 8: Preference Parameters

	Return		Stability	
	Estimate	Standard Error	Estimate	Standard Error
	Non-college			
f_0	-5.155	0.121	-1.576	0.108
$F_{1,\text{Black}}$	-0.194	0.044	-0.023	0.04
$F_{1,\text{Male}}$	0.401	0.044	-0.068	0.038
$F_{1,\text{AFQT}}$	0.11	0.042	0.031	0.039
F_2	3.196	0.116	1.331	0.089
F_3	-7.146	0.127	-5.682	0.1
$\overline{y}_0$	0.317	0.037	0.514	0.04
$Y_{1,\text{Black}}$	0.012	0.022	0.026	0.023
$Y_{1,\text{Male}}$	0.115	0.02	-0.063	0.022
$Y_{1,\text{AFQT}}$	-0.007	0.021	0.004	0.022
$Y_{1,\gamma}$	0	0.005	0.003	0.006
	College			
f_0	-6.664	0.165	-0.445	0.134
$F_{1,\text{Black}}$	-0.029	0.07	0.045	0.068
$F_{1,\text{Male}}$	0.096	0.063	0.024	0.059
$F_{1,\text{AFQT}}$	0.412	0.065	0.157	0.063
F_2	5.012	0.145	0.518	0.103
F_3	-8.015	0.174	-7.786	0.163
$\overline{y}_0$	0.456	0.038	0.446	0.041
$Y_{1,\text{Black}}$	0.002	0.025	0.032	0.027
$Y_{1,\text{Male}}$	0.058	0.022	-0.037	0.024
$Y_{1,\text{AFQT}}$	0.027	0.024	-0.062	0.026
$Y_{1,\gamma}$	0	0.005	0.014	0.005

Source.–National Longitudinal Survey of Youth 1997

Note.–The estimates are for non-pecuniary preference and initial occupation propensity. 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 $y_0 = \overline{y}_0 + Y_1(x', \gamma)'$.

Table 9: Earnings Gap Decomposition - Lifetime Earnings Relative to Most Averse

	Data	Baseline (1)	No Initial (2)	(1)-(3)	No Accum. (4)	(2)-(4)
				Non-college		
Lifetime Earnings Gap	0.143	0.140	0.042	0.098	0.023	0.019
% of Baseline		(100)	(30)	(70)	(16)	(14)
				College		
Lifetime Earnings Gap	0.176	0.235	0.077	0.158	0.04	0.037
% of Baseline		(100)	(33)	(67)	(17)	(16)

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, Table 7, and Table 8 and their variations. The simulated data are 100 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 Subsection 6.2.

Table 10: Counterfactual under Social Insurance
Occupation Allocation - Non-college Sample

	Baseline	With SI	*Change*
		Expected Return	
Average (pctl)	0.511	0.508	*-0.003*
Tolerant	0.569	0.537	*-0.032*
Averse	0.498	0.501	*0.003*
Gap	0.072	0.036	*-0.036*
		Earnings Stability	
Average (pctl)	0.531	0.53	*-0.001*
Tolerant	0.505	0.513	*0.008*
Averse	0.536	0.534	*-0.002*
Gap	-0.031	-0.021	*0.01*

Note.–The table reports average occupational characteristics for the whole sample and by risk attitude groups from the data simulated with the earnings floor as $9.3. The parameter estimates used in the simulation are available in Table 6, Table 7, and Table 8. The simulated data are 100 times the size of the real data. A detailed description of the simulations is provided in Section 7.

Table 11: Counterfactual under Social Insurance
Earnings and Outputs - Non-college Sample

	Baseline	Occ. with Floor			
Log (Hourly) Earnings		w/o Floor	Δ	w/ Floor	Δ
Average	2.64	2.64	*0*	2.69	*0.05*
Tolerant	2.76	2.74	*-0.02*	2.77	*0.01*
Averse	2.62	2.62	*0*	2.67	*0.05*
Gap	0.14	0.12	*-0.02*	0.10	*-0.04*
Log Total Outputs	16.908	16.906	*-0.002*		

Note.–The table reports average log earnings for the whole sample and by risk attitude groups and log total outputs from the data simulated with the earnings floor as $9.3. Earnings in the counterfactual are defined both with and without the realization of the earnings floor, keeping occupation choices with the earnings floor. The change in earnings is the difference between the baseline and the counterfactual earnings. The parameter estimates used in the simulation are available in Table 6, Table 7, and Table 8. The simulated data are 100 times the size of the real data. A detailed description of the simulations is provided in Section 7.

Table 12: Counterfactual under Social Insurance
Occupation Allocation - College Sample

	Baseline	With SI	*Change*
		Expected Return	
Average (pctl)	0.652	0.647	*-0.005*
Tolerant	0.717	0.677	*-0.04*
Averse	0.626	0.635	*0.009*
Gap	0.091	0.042	*-0.049*
		Earnings Stability	
Average (pctl)	0.481	0.485	*0.004*
Tolerant	0.425	0.456	*0.031*
Averse	0.504	0.497	*-0.007*
Gap	-0.079	-0.04	*0.039*

Note.–The table reports average occupational characteristics for the whole sample and by risk attitude groups from the data simulated with the earnings floor as $9.3. The parameter estimates used in the simulation are available in Table 6, Table 7, and Table 8. The simulated data are 100 times the size of the real data. A detailed description of the simulations is provided in Section 7.

Table 13: Counterfactual under Social Insurance
Earnings and Outputs - College Sample

	Baseline	Occ. with Floor			
Log (Hourly) Earnings		w/o Floor	Δ	w/ Floor	Δ
Average	3.06	3.05	*-0.01*	3.06	*0*
Tolerant	3.23	3.2	*-0.03*	3.2	*-0.03*
Averse	2.99	3	*0.01*	3.01	*0.02*
Gap	0.24	0.2	*-0.04*	0.19	*-0.05*
Log Total Outputs	16.858	16.852	*-0.006*		

Note.–The table reports average log earnings for the whole sample and by risk attitude groups and log total outputs from the data simulated with the earnings floor as $9.3. Earnings in the counterfactual are defined both with and without the realization of the earnings floor, keeping occupation choices with the earnings floor. The change in earnings is the difference between the baseline and the counterfactual earnings. The parameter estimates used in the simulation are available in Table 6, Table 7, and Table 8. The simulated data are 100 times the size of the real data. A detailed description of the simulations is provided in Section 7.

A Estimation Algorithm: EM algorithm with CCP estimator

In this section, I provide details of the estimation process. I first impute the relative risk aversion coefficient for each group of lottery choices. Then, I explain the EM algorithm with CCP estimators which includes the derivation of the posterior distribution of unobserved state variables, the update of conditional choice probabilities, and the maximization problem. In the expectation step, the CCP's are updated using the matrix inversion method from Hotz and Miller (1993). The distribution of unobserved skills 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 as if unobserved states are observed using the posterior distribution of unobserved skills as weights. This allows the log-likelihood to be additively separable, and thus the maximization problem will be separated into multiple stages.

A.1 Estimating Relative Risk Aversion from Lottery Choice

To estimate the relative risk aversion coefficient for each risk attitude group, I assume the coefficient of risk tolerance ($\kappa = 1/\gamma$, reciprocal of risk aversion) follows the log-normal distribution. Since the gamble survey was asked without any tangible incentive, I further assume the logarithm of the relative risk aversion coefficient in the lottery choice involves a noise with normal distribution:

$$\begin{aligned} &\ln \kappa^* = \ln \kappa + \nu \\ &\ln \kappa \sim N(\mu, \sigma_\kappa^2), \quad \nu \sim N(0, \sigma_g^2) \end{aligned} \tag{A.1}$$

With their relative risk aversion given as $\gamma^* = (1/\kappa^*)$, workers answered the gamble choice survey 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:[A1]

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

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

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

Under the CRRA assumption, these inequalities can be reduced into the intervals with respect to κ^*. For example, for the moderate tolerant group with $g = (0,1)$, κ^* should be between 0.27 and 0.5. The upper and the lower bound of κ^* for each inequality is summarized in Table A1. Denoting the upper and the lower bound of κ given g as $(\overline{\kappa}(g), \underline{\kappa}(g))$, the likelihood of lottery choice can be formulated with the log normal distribution of κ^*:

$$P(g;\mu,\sigma_\gamma,\sigma_g) = \Phi\left(\frac{\overline{\kappa}(g) - \mu}{\sqrt{\sigma_\kappa^2 + \sigma_g^2}}\right) - \Phi\left(\frac{\underline{\kappa}(g) - \mu}{\sqrt{\sigma_\kappa^2 + \sigma_g^2}}\right) \tag{A.4}$$

[A1] 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.

where Φ represents the cumulative distribution function of the standard normal distribution. Then, the maximum likelihood estimator can be defined as

$$(\hat{\mu}, \hat{\sigma}_\kappa, \hat{\sigma}_g) = \underset{(\mu,\sigma_\kappa,\sigma_g)}{\arg\max} \sum_i P(g_i; \mu, \sigma_\kappa, \sigma_g) \tag{A.5}$$

With one time survey of hypothetical gamble choices, σ_κ and σ_g are not separately identifiable. However, Kimball et al. (2008) documents that the gamble responses are subject to significant measurement errors. Following Kimball et al. (2009), I impose the estimate of the variance of true log tolerance from Kimball et al. (2008) who uses the same gamble responses from the Health and Retirement Survey (HRS). Since the sample of the NLSY97 is younger than that of the HRS, I allow the mean of log tolerance to be freely estimated. Given $\hat{\sigma}_\kappa = 0.76$, the estimates of the parameters are $\hat{\mu} = -1.35$ and $\hat{\sigma}_g = 0.9$.[A2]

Using the estimated distribution of log tolerances and measurement errors, I impute the expected value of relative risk aversion conditional on their survey responses. I use the conditional moment-generating function of log-normal distribution:

$$E\left[\gamma|g\right] = \exp\left(-\mu + \frac{\sigma_\kappa^2}{2}\right)\left[\frac{\Phi\left(\frac{\overline{\kappa}(g)-\mu+\sigma_\kappa^2}{\sqrt{\sigma_\kappa^2+\sigma_g^2}}\right) - \Phi\left(\frac{\underline{\kappa}(g)-\mu+\sigma_\kappa^2}{\sqrt{\sigma_\kappa^2+\sigma_g^2}}\right)}{\Phi\left(\frac{\overline{\kappa}(g)-\mu}{\sqrt{\sigma_\kappa^2+\sigma_g^2}}\right) - \Phi\left(\frac{\underline{\kappa}(g)-\mu}{\sqrt{\sigma_\kappa^2+\sigma_g^2}}\right)}\right] \tag{A.6}$$

The imputed relative risk aversion for each group is also provided in Table A1. Given these values as individual relative risk aversion, I estimate the rest of the model parameters using the EM algorithm with CCP estimators. The following subsections provide greater details of the $(m+1)$th iteration given the mth estimates of CCP's and parameters.

[A2]Kimball et al. (2009) use the same method of estimation and the estimates are $\hat{\mu} = -1.05$ and $\hat{\sigma}_g = 1.69$.

A.2 Expectation: CCP's and Distribution of Unobserved States

For notation, a vector of model parameters, θ, consists of three components that determine 1) the distribution of unobserved skills and their transition (θ_u), 2) wages (θ_w), and 3) non-pecuniary preference (θ_p). Also, define $\theta_{-u} = (\theta_w, \theta_p)$, the model parameters other than θ_u.

Given the mth parameter and CCP estimates $(\theta^{(m)}, \hat{P}^{(m)})$ and observed outcomes Z_i, I first update $p_{it}(s)$, the probability of i having skill s at period t. Then, I update $\psi_1(s_1|x_i)$, 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, I close the expectation step by updating CCP estimates.

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

$$\begin{aligned} l_t^*(Z_i, s_{it} = s|\gamma, x_i) = &\sum_{s_1} \cdots \sum_{s_{t-1}} \sum_{s_{t+1}} \cdots \sum_{s_T} \psi_1(s_1|x_i) l_1(z_{i1}|s_1, \gamma, x_i) \\ &\times \left(\prod_{\tau=2}^{t-1} \psi(s_\tau|s_{\tau-1}, x_i, j_{i,\tau-1}) l(z_{i\tau}|s_\tau, \gamma, x_i, j_{i,\tau-1}) \right) \\ &\times \psi(s|s_{t-1}, x_i, j_{i,t-1}) l(z_{it}|s, \gamma, x_i, j_{i,t-1}) \psi(s_{t+1}|s, x_i, j_{i,t}) l(z_{it}|s_{t+1}, \gamma, x_i, j_{i,t}) \\ &\times \left(\prod_{\tau=t+2}^{T} \psi(s_\tau|s_{\tau-1}, x_i, j_{i,\tau-1}) l(z_{i\tau}|s_\tau, \gamma, x_i, j_{i,\tau-1}) \right) \end{aligned} \tag{A.7}$$

Given the individual likelihood of labor market profile as (22), Bayes' rule implies the conditional probability of i being in unobserved skill s at period t as

$$p_{it}^{(m+1)}(s) = \frac{l_t^*(Z_i, s_{it} = s|\gamma_i, x_i)}{l^*(Z_i|\gamma_i, x_i)} \tag{A.8}$$

Update $\psi_1(s_1|x_i, \gamma_i)$ **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, $p_{i1}^{(m+1)}$:[A3]

$$H_1^{(m+1)} = \arg\max_{H_1} \sum_i \int p_{i1}^{(m+1)}(s) \log \psi(s|x_i, \gamma_i) ds \tag{A.9}$$

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}) 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 $p_{it-1}(s_{t-1})$. The former is calculated as follows:

$$\begin{aligned}
\tilde{l}_{it}^{(m+1)}(s|s_{t-1}) =& \psi^{(m)}(s|s_{t-1}, x_i, j_{i,t-1}) l(z_{it}|s, \gamma_i, x_i, j_{i,t-1}) \\
& \times \left(\sum_{s_{t+1}} \cdots \sum_{s_T} \psi^{(m)}(s_{t+1}|s, x_i, j_{i,t-1}) l(z_{it+1}|s_{t+1}, \gamma_i, x_i, j_{i,t}) \right. \\
& \left. \times \prod_{\tau=t+2}^{T} \psi^{(m)}(s_\tau|s_{\tau-1}, x_i, j_{i,\tau-1}) l(z_{i\tau}|s_\tau, \gamma_i, x_i, j_{i,\tau}) \right) \\
\tilde{p}_{2it}^{(m+1)}(s|s_{t-1}) =& \frac{\tilde{l}_{it}^{(m+1)}(s|s_{t-1})}{\sum_{s_t} \tilde{l}_{it}^{(m+1)}(s_t|s_{t-1})}
\end{aligned} \tag{A.10}$$

Given $p_{it-1}^{(m+1)}(s)$ and $\tilde{p}_{2it}^{(m+1)}(s'|s)$, equation (10) can be estimated by the following maximum likelihood estimation:[A4]

$$\begin{aligned}
&\theta_s^{(m+1)} = \\
&\arg\max_{\theta_s} \sum_i \sum_{t=2} \iint \left(p_{it-1}^{(m+1)}(s|\gamma) \tilde{p}_{2it}^{(m+1)}(s'|s) \right) \log \psi(s'|s, x_i, j_{i,t-1}; \theta_s) ds ds'
\end{aligned} \tag{A.11}$$

where θ_s represents a vector of skill transition parameters.

Update CCPs Given the CCP estimates as $\hat{P}$, the derivation of CCP's directly follows the matrix

[A3] In actual estimation, the integral is replaced with the summation as skills are discretized.
[A4] In actual estimation, integrals are replaced with summations as skills are discretized.

inversion method of Hotz and Miller (1993). 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

$$\overline{V} = \left(I - \beta \sum_j (P_j \vec{\mathbf{1}}') \odot F_j \right)^{-1} \left(\sum_j P_j \odot (U_j + \epsilon_j^*) \right) \tag{A.12}$$

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 $\hat{P}^{(m)}$ and parameters $\theta^{(m)}$, the optimal policy of occupation choices can be constructed using equation (16) and (18): for all j,

$$\hat{P}^{(m+1)}(j|s_{it}, \gamma_i, x_i, j_{i,t-1}; \hat{P}^{(m)}, \theta^{(m)}) = \frac{\exp(v_j(s_{it}, \gamma_i, x_i, j_{i,t-1}; \hat{P}^{(m)}, \theta^{(m)}))}{\sum_{j'} \exp(v_{j'}(s_{it}, \gamma_i, x_i, j_{i,t-1}; \hat{P}^{(m)}, \theta^{(m)}))} \tag{A.13}$$

A.3 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.

$$\max_\theta \sum_i \sum_t \sum_s \left[p_{it}^{(m+1)}(s) \log \left(l(z_{it}|s, \gamma_i, x_i, j_{i,t-1}; (\theta_u^{(m+1)}, \theta_{-u})) \right) \right] \tag{A.14}$$

In Subsection A.4, I prove that the maximization problem above is equivalent to maximizing the sum of individual log-likelihood presented by equation (22). 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 in the estimation with heavy computation. More details on the maximization step are provided in Subsection A.4.

A.4 Equivalence of Two Maximization Problems

In this subsection, 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 over the whole career. As a reminder, Z_i represents the observed labor market profiles, $l(Z|s, \gamma_i, x_i; \theta)$ refers to the likelihood of Z given unobserved skills as s, and $l^*(Z|\gamma_i, x_i; \theta)$ refers to the observed likelihood after integrating out unobserved skills, defined in (22).

Given the estimated CCPs and the distribution of unobserved heterogeneity, θ_{-u} can be updated by maximizing:

$$LL(\theta_{-u}) = \sum_i \log l^*(Z_i|\gamma_i, x_i; \hat{P}, (\theta_u, \theta_{-u})) \tag{A.15}$$

For exposition, $\hat{P}$ and θ_u are omitted henceforth. The first order condition of maximizing (A.15) is

$$\begin{aligned} 0 &= \sum_i \frac{1}{l^*(Z_i|\gamma_i, x_i; \theta_{-u})} \sum_s \psi(s|x_i, \gamma_i) \frac{\partial}{\partial \theta_{w,p}} l(Z_i|s, \gamma_i, x_i; \theta_{-u}) \\ &= \sum_i \sum_s \frac{\psi(s|x_i, \gamma_i) l(Z_i|s, \gamma_i, x_i; \theta_{-u})}{l^*(Z_i|\gamma, x_i; \theta_{-u})} \frac{\partial}{\partial \theta_{w,p}} \log l(Z_i|s, \gamma_i, x_i; \theta_{-u}) \\ &= \sum_i \sum_s p_i(s) \frac{\partial}{\partial \theta_{w,p}} \log l(Z_i|s, \gamma_i, x_i; \theta_{-u}) \end{aligned} \tag{A.16}$$

where $p_i(s)$ refers to the conditional probability of individual i being in unobserved state s. In other words, given $p_i(s)$, maximizing (A.15) is equivalent to the following optimization problem.

$$\hat{\theta}_{-u} = \arg\max_{\theta_{-u}} \sum_i \sum_s p_i(s) \log l(Z_i|s, \gamma_i, x_i; \theta_{-u}) \tag{A.17}$$

Provided that unobserved skill is given, the log-likelihood of occupation choice and wage is 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).

A.5 Additional Estimation Setting

Earnings utility function has earnings rescaled to unit variance as its input and it is relocated so that earnings utility becomes zero when hourly rate is the minimum value, \$1. When earnings are scaled in natural units, marginal utility over earnings becomes almost negligible, implying earnings generally have no effect on occupation decisions. In addition, utility over earnings drastically changes in the negative ranges, making computation unstable. Rescaling and relocation helps ensure the reasonable variation of earnings utility to rationalize the observed earnings and occupation choices. Formally speaking, given the standard deviation of hourly earnings rate as σ_{Earn}, utility from earnings becomes as follows:

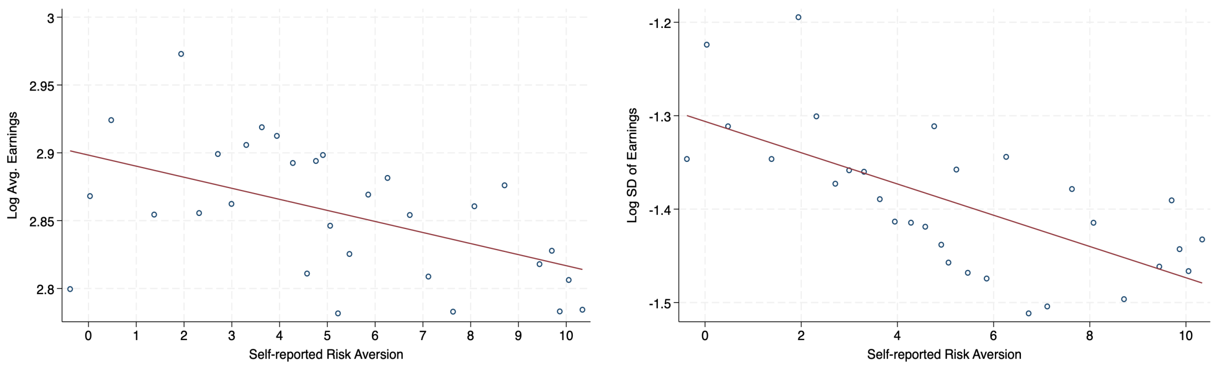
$$u(w;\gamma) = \frac{\left(\frac{w+\sigma_{\text{Earn}}-1}{\sigma_{\text{Earn}}}\right)^{1-\gamma} - 1}{1-\gamma} \tag{A.18}$$

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. 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 third-order polynomials of skills for each iteration of the likelihood function.

Table A1: Boundaries of Risk Tolerance and Imputed Risk Aversion

Group	g	Choice	Lower bound of κ	Upper bound of κ	$\hat{\gamma}_g$
Most Tolerant	$(0, 0)$	Risky-More Risky	1	∞	2.11
Tolerant	$(0, 1)$	Risky-Safe	0.5	1	3.08
Averse	$(1, 0)$	Safe-Less Risky	0.27	0.5	3.99
Most Averse	$(1, 1)$	Safe-Safe	0	0.27	6.92

B Additional Figures and Tables



(a) Lifetime Average Earnings

(b) Lifetime Earnings Volatility

Figure B1: Self-reported Risk Attitudes and Labor Market Outcomes

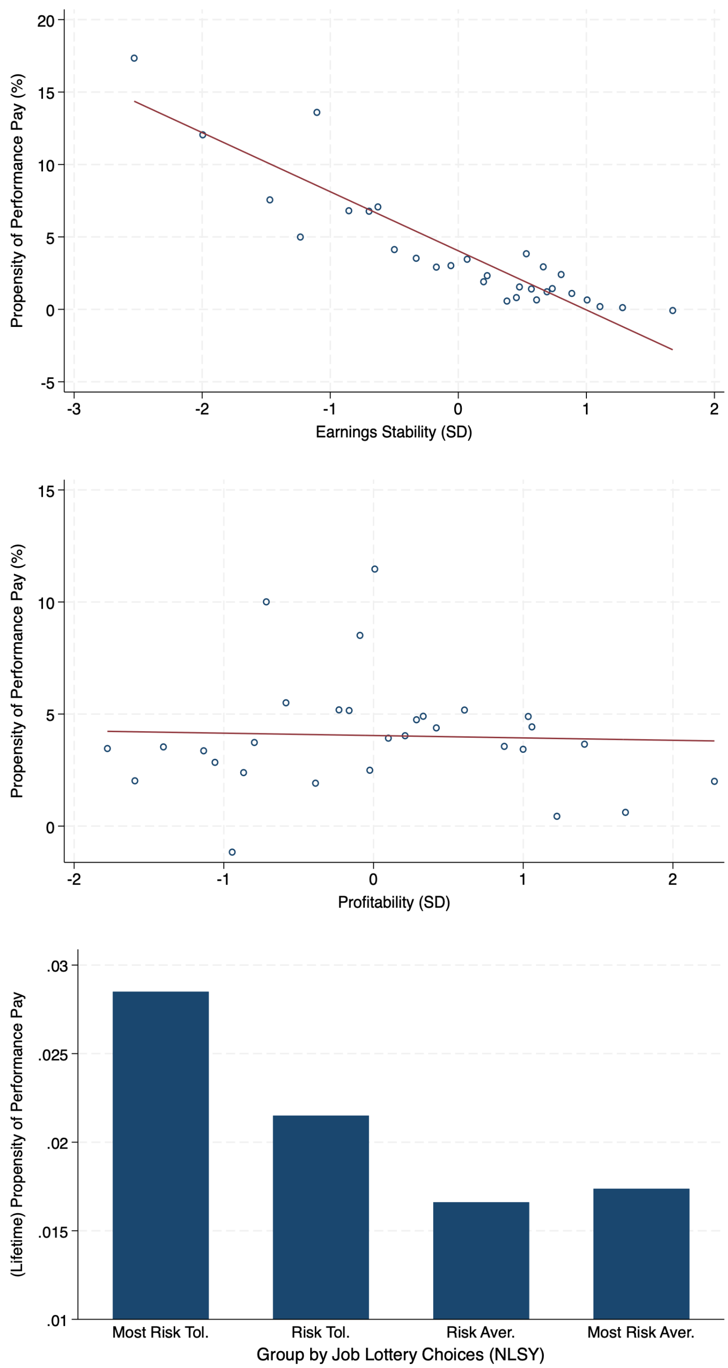


Figure B2: Performance Pay, Earnings Risks, and Risk Aversion

Table B2: List of 3-digit Occupations

SOC3	Title	SOC3 New	Title
111	Top Executives	111	Top Executives
112	Advertising, Marketing, Promotions, Public Relations, and Sales Managers	112	Advertising, Marketing, Promotions, Public Relations, 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	132	Financial Specialists
151	Computer Occupations	151	Computer Occupations
152	Mathematical Science Occupations	152	Mathematical Science Occupations
171	***Architects, Surveyors, and Cartographers***	***173***	***Drafters, Engineering Technicians, and Mapping Technicians***
172	Engineers	172	Engineers
173	Drafters, Engineering Technicians, and Mapping Technicians	173	Drafters, Engineering Technicians, and Mapping Technicians
191	Life Scientists	191	Life 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	Counselors, Social Workers, and Other Community and Social Service Specialists	211	Counselors, Social Workers, and Other Community and Social Service Specialists
212	Religious Workers	212	Religious Workers
231	Lawyers, Judges, and Related Workers	231	Lawyers, Judges, and Related Workers
232	Legal Support Workers	232	Legal Support Workers
251	Postsecondary Teachers	251	Postsecondary Teachers
252	Preschool, Elementary, Middle, Secondary, and Special Education Teachers	252	Preschool, Elementary, Middle, Secondary, and Special Education Teachers
253	Other Teachers and Instructors	253	Other Teachers and Instructors
254	Librarians, Curators, and Archivists	254	Librarians, Curators, and Archivists
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
299	***Other Healthcare Practitioners and Technical Occupations***	***292***	***Health Technologists and Technicians***
311	Home Health and Personal Care Aides; and Nursing Assistants, Orderlies	311	Home Health and Personal Care Aides; and Nursing Assistants, Orderlies
312	Occupational Therapy and Physical Therapist Assistants and Aides	312	Occupational Therapy and Physical Therapist Assistants and Aides
319	***Other Healthcare Support Occupations***	***312***	***Occupational Therapy and Physical Therapist Assistants and Aides***
331	Supervisors of Protective Service Workers	331	Supervisors of Protective Service Workers
332	Firefighting and Prevention Workers	332	Firefighting and Prevention 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	353	Food and Beverage Serving Workers
359	Other Food Preparation and Serving Related Workers	359	Other Food Preparation and Serving Related Workers
371	Supervisors of Building and Grounds Cleaning and Maintenance Workers	371	Supervisors of Building and Grounds 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
391	***Supervisors of Personal Care and Service Workers***	***399***	***Other Personal Care and Service Workers***
392	Animal Care and Service Workers	392	Animal Care and Service Workers
393	Entertainment Attendants and Related Workers	393	Entertainment Attendants and Related Workers
394	***Funeral Service Workers***	***399***	***Other Personal Care and Service Workers***
395	Personal Appearance Workers	395	Personal Appearance Workers
396	Baggage Porters, Bellhops, and Concierges	396	Baggage Porters, Bellhops, and Concierges
399	Other Personal Care and Service Workers	399	Other Personal Care and Service Workers

Table B2 continued from previous page

SOC3	Title	SOC3 New	Title
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	414	Sales Representatives, Wholesale and Manufacturing
419	Other Sales and Related Workers	419	Other Sales and Related Workers
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	433	Financial Clerks
434	Information and Record Clerks	434	Information and Record Clerks
435	Material Recording, Scheduling, Dispatching, and Distributing Workers	435	Material Recording, Scheduling, Dispatching, and Distributing Workers
436	Secretaries and Administrative Assistants	436	Secretaries and Administrative Assistants
439	Other Office and Administrative Support Workers	439	Other Office and Administrative Support Workers
451	***Supervisors of Farming, Fishing, and Forestry Workers***	***452***	***Agricultural Workers***
452	Agricultural Workers	452	Agricultural Workers
453	***Fishing and Hunting Workers***	***452***	***Agricultural Workers***
454	***Forest, Conservation, and Logging Workers***	***452***	***Agricultural Workers***
471	Supervisors of Construction and Extraction Workers	471	Supervisors of Construction and Extraction Workers
472	Construction Trades Workers	472	Construction Trades Workers
473	Helpers, Construction Trades	473	Helpers, Construction Trades
474	Other Construction and Related Workers	474	Other Construction and Related Workers
475	Extraction Workers	475	Extraction Workers
491	Supervisors of Installation, Maintenance, and Repair Workers	491	Supervisors of Installation, Maintenance, and Repair Workers
492	Electrical and Electronic Equipment Mechanics, Installers, and Repairers	492	Electrical and Electronic Equipment Mechanics, Installers, and Repairers
493	Vehicle and Mobile Equipment Mechanics, Installers, and Repairers	493	Vehicle and Mobile Equipment Mechanics, Installers, and Repairers
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	515	Printing Workers
516	Textile, Apparel, and Furnishings Workers	516	Textile, Apparel, and Furnishings Workers
517	Woodworkers	517	Woodworkers
518	***Plant and System Operators***	***519***	***Other Production Occupations***
519	Other Production Occupations	519	Other Production Occupations
531	Supervisors of Transportation and Material Moving Workers	531	Supervisors of Transportation and Material Moving Workers
532	***Air Transportation Workers***	***536***	***Other Transportation Workers***
533	Motor Vehicle Operators	533	Motor Vehicle Operators
534	***Rail Transportation Workers***	***536***	***Other Transportation Workers***
535	***Water Transportation Workers***	***536***	***Other Transportation Workers***
536	Other Transportation Workers	536	Other Transportation Workers
537	Material Moving Workers	537	Material Moving Workers

Note.–Bold and italic are 3-digit codes that are merged to the closest one within the same 2-digit code.

Table B3: Adaptive Lasso Regression

Earnings Stability	
Communicating with Supervisors, Peers, or Subordinates	0.116
Thinking Creatively	-0.104
Degree of Automation	0.101
Selling or Influencing Others	-0.082
Mathematical Reasoning	0.058
Spend Time Walking or Running	0.039
Explosive Strength	0.037
Number Facility	0.03
Monitor Processes, Materials, and Surroundings	0.013
R^2	0.59
Expected Return	
Level of Competition	0.1
Spend Time Walking or Running	-0.1
Wear Specialized Protective or Safety Equipment	0.073
Interpreting the Meaning of Information for Others	0.037
Visualization	0.036
Impact of Decisions on Coworkers or Company Results	0.029
R^2	0.61

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

Note.–Earnings stability and return are regressed on O*NET items in ability, skill, activity, and context fields using adaptive Lasso algorithm at the 81 occupation level.

Table B4: 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***	0.085***	0.114***	0.095***	0.093***
	(0.016)	(0.015)	(0.015)	(0.027)	(0.027)	(0.028)
Tolerant	0.060***	0.058***	0.058***	0.059*	0.057*	0.049
	(0.018)	(0.016)	(0.016)	(0.031)	(0.030)	(0.030)
Averse	0.036***	0.029**	0.029**	0.039	0.027	0.021
	(0.013)	(0.012)	(0.012)	(0.024)	(0.024)	(0.024)
Demographics	✓	✓	✓	✓	✓	✓
Major Occupation		✓	✓		✓	✓
2nd Major Occupation			✓			✓
N	4,188	4,188	4,188	4,177	4,177	4,177
R^2	0.359	0.475	0.522	0.048	0.101	0.121

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 and major occupation fixed effects. Control variables include race, gender, AFQT scores, and education levels. Robust standard errors in parenthesis.

Table B5: Risk Aversion and Occupation Choice with Alternative Measures

	Stability			Return
	(1)	(2)	(3)	(4)
Most Tolerant	-0.03***	-0.04***	-0.04***	0.03***
	(0.01)	(0.01)	(0.01)	(0.01)
Tolerant	-0.02**	-0.02**	-0.02**	0.02**
	(0.01)	(0.01)	(0.01)	(0.01)
Averse	-0.01*	-0.02**	-0.02**	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)
Measure	$\exp(\upsilon)^2$	Trend	Occ Tenure	Raw Average
N	48,253	48,253	48,253	48,253
R^2	0.03	0.04	0.04	0.23

Source.–National Longitudinal Survey of Youth 1997

Note.–The estimates are from the regression of alternative measures of earnings stability and return on risk attitude group indicators. Control variables include race, gender, age-adjusted AFQT scores and education level. First three columns use alternative measures of earnings stability; Column (1) uses mean squared of exponential residuals, (2) uses mean squared of residuals from earnings regression with quadratic time trend instead of period fixed effects, (3) uses mean squared of residuals from earnings regression with occupation-specific return to tenures. Column (4) uses raw average of earnings within occupations as alternative measure of earnings returns. Standard errors clustered at individual-occupation level.

Table B6: Risk Aversion and Lifetime Earnings by Groups (Base: Most Averse)

	Gender		Race		Education	
	Women	Men	Black	Non-Black	High School	College
	Log Average Earnings					
Most Tolerant	0.06***	0.15***	0.10***	0.11***	0.12***	0.12***
	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)
Tolerant	0.08***	0.07***	0.09***	0.06***	0.10***	0.06*
	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)
Averse	0.04**	0.02	0.00	0.04***	0.02	0.06**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
	Log SD of Log Earnings					
Most Tolerant	0.07	0.19***	0.10	0.16***	0.14***	0.15***
	(0.05)	(0.04)	(0.07)	(0.03)	(0.04)	(0.04)
Tolerant	0.06	0.11**	0.02	0.11***	0.12***	0.07
	(0.05)	(0.04)	(0.07)	(0.04)	(0.05)	(0.05)
Averse	0.05	0.11***	0.04	0.10***	0.05	0.14***
	(0.04)	(0.03)	(0.05)	(0.03)	(0.03)	(0.04)

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 for each subgroup. Control variables include race, gender, AFQT scores, and education levels. Robust standard errors in parenthesis.

Table B7: Risk Aversion and Occupation Choice by Groups (Base: Most Averse)

	Gender		Race		Education	
	Women	Men	Black	Non-Black	High School	College
	Earnings Return					
Most Tolerant	0.01	0.04***	0.02	0.03***	0.03**	0.04***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
Tolerant	0.02	0.02*	0.02	0.01	0.03**	0.01
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
Averse	-0.01	-0.00	0.01	-0.01	-0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
	Earnings Stability					
Most Tolerant	-0.02*	-0.04***	-0.05***	-0.03***	-0.04***	-0.04***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
Tolerant	-0.04***	-0.02	-0.05***	-0.02	-0.02	-0.03**
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
Averse	-0.02*	-0.01	-0.02	-0.02*	-0.02*	-0.02*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)

Source.–National Longitudinal Survey of Youth 1997

Notes.–The estimates are from the regression of earnings stability and return measures on risk attitude group indicators for each subgroup. Control variables include race, gender, AFQT scores, and education levels. Robust standard errors in parenthesis.