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Frictions in the Youth Labor Market: Theory and Evidence

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Frictions in the Youth Labor Market: Theory and Evidence

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Abstract

This dissertation investigates how young workers' abilities shape their early careers in the presence of information frictions and labor market shocks through two studies. The research in the first chapter focuses on the strength of a worker's comparative advantage, which measures the distribution of her abilities. Workers are uncertain about what they are good at when they enter the labor market, and then they shop around to find their best-matched occupations. I use the average distance between productivities in the best-matched occupation and the other occupations to measure the strength of a worker's comparative advantage. Empirically, those productivities are estimated from a multinomial logit regression of a worker's choice of her best-matched occupations. A worker with a larger productivity distance has a stronger comparative advantage. The empirical results suggest that this worker spends fewer years shopping occupations and tries fewer occupations before finding her best-matched one. To further quantify the importance of strength in occupational shopping, I build a learning model in which a worker determines her comparative advantage by observing the output at the current occupation. The quantitative model suggests that enlarging the productivity distance by one standard deviation in the model reduces more than 80% of occupational changes in the first ten years of careers. Moreover, for an average labor market entrant, the value of learning about her comparative advantage is 28% of her expected lifetime earning.

The study in the second chapter focuses on how Conscientiousness, a personality trait, helps workers mitigate the adverse effects of graduating during a recession on early career outcomes. By analyzing college graduates who graduated in the 1980s, I find that Conscientiousness reduces the income losses of workers who graduate during a recession. More specifically, those whose Conscientiousness scores are in the upper quartile are sheltered from the losses. The mitigation effect primarily results from workers' adjustments in their labor supply. Workers high in Conscientiousness tend to work more weeks, try harder to find full-time jobs, and work more hours in these full-time jobs in response to the adverse labor market entry conditions. However, this study does not find any mitigation effects for cognitive ability.

Dedication

To my beloved grandparents, Shengdao, Xianlan, Jinyi, and Fanglan.

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Chapter 1

Occupational Shopping of Youth: The Strength of a Worker's Comparative Advantage

1.1 Introduction

This study explores how the strength of a worker's comparative advantage influences her occupational choices and the path to her best-matched occupation in her early career. Occupational choice plays a significant role in the wage growth of young workers, with a mismatch between workers and occupations depressing the wage growth not only in the current occupation but also in future ones (Guvenen et al., 2020; Addison, Chen and Ozturk, 2019).

A worker is uncertain about her most appropriate occupation when she enters the labor market. She learns it while at work and changes occupations as she discovers ones more suitable. Previous literature has found that this learning process is one key element driving occupational changes (Johnson, 1978; Antonovics and Golan, 2012; Papageorgiou, 2014; Gorry, Gorry and Trachter, 2019). Based on the previous research, this paper proposes that a worker who has a stronger comparative advantage is easier to find her best-matched occupation because she needs less information to discover the best-matched one. This study uses the average distance between the productivity in a worker's best-matched occupation and the productivity in her other occupations to measure the strength of her comparative advantage. For this measurement, a shorter average distance indicates an more even productivity distribution and a weaker comparative advantage.

Using a subsample of high school graduates from the National Longitudinal Survey of Youth 1979 (NLSY79), this study finds that a young worker who has a stronger comparative advantage takes a shorter time and tries fewer occupations before she finds the one best suited for her. The productivity used to measure the strength of the comparative advantage defined above is unobserved in the data. This study estimates it using a multinomial logit regression of the final occupational choice at the end of the first ten years. In this estimation, I assume that workers complete the occupational learning process after ten years of working experience and are in their best-matched occupations at that time. My quantitative model is consistent with this assumption, suggesting that approximately 90% of workers find the ones best suited for them at the end of the first ten years.

To further quantify the importance of the strength of a worker's comparative advantage and the value of learning her most appropriate occupation, I build a learning model of occupational choices with heterogeneous occupation-specific productivity. My model builds on the canonical job shopping model of Johnson (1978), extending his framework to a dynamic model with three occupations. Following Papageorgiou (2014), I assume that workers have three occupation-specific productivities instead of one general ability as assumed by Johnson (1978). The productivity of each occupation is drawn from a separate normal distribution. A worker does not know her productivities at labor market entry and chooses an occupation to work in each period to maximize her expected lifetime income. The worker only learns about her productivity in the current occupation by observing her noisy output. The policy function of my model is given by the Gittins Index, which characterizes the total value of wage and learning. A worker's optimal choice is to work in the occupation with the highest Gittins Index in each period (Gittins, 1979). For a worker with evenly distributed occupation-specific productivities, a small change in the current occupation's Gittins Index caused by learning, is likely to make the current occupation suboptimal in the next period, thus leading to an occupational change.

In this study, the model is calibrated by matching moments of wages and occupational changes during the first two years of careers. The simulated model developed here is consistent with the patterns of occupational changes in the first ten years in the data, including the declining probability of occupational switches, asymmetric occupational transition matrix, and return mobility. The model also replicates the effects of the productivity distance on the path to a worker's best-matched occupation in the data. Workers in the model with shorter distances between occupation-specific productivities also take longer and try more occupations before moving to their best-matched occupations than their counterparts with longer distances.

The model quantifies the importance of heterogeneous occupation-specific productivity for occupational changes of young workers. In a counterfactual exercise, I increase the distance between productivities by one standard deviation. The comparison between the experimental and the calibrated models reveals that the increase in the distance reduces more than 80% of simulated occupational changes in the first ten years. My model also quantifies the value a worker ascribes to learning her appropriate occupation. The value placed on this learning is 28% of the expected lifetime earnings for an average labor market entrant and decreases to 4% for an average worker with ten years of labor market experience.

This paper is the first to study the interaction between the strength of comparative advantage and the learning process and to document the effects of strength on occupational changes. It contributes to the literature on how a worker's learning drives occupational transitions.[1] Johnson (1978) began the research in this area by exploring the effects of learning on job choice for workers who are uncertain about their general ability. He finds that young workers trade the current wage for an extra amount of learning and choose riskier jobs initially. Recent papers have extended this research by exploring various abilities that workers learn about (Antonovics and Golan, 2012; Papageorgiou, 2014; Groes, Kircher and Manovskii, 2015; Gorry, Gorry and Trachter, 2019). In addition to their abilities, workers could also learn their match qualities, a factor driving job or occupational changes as well (Jovanovic, 1979; Miller, 1984; McCall, 1990; Neal, 1999).

This research is most closely related to Papageorgiou (2014). Following his paper, workers in my model have multi-dimensional abilities and learn their comparative advantages over time. However, I abstract from the correlations between occupation-specific productivities and search frictions to emphasize the effects of the productivity distribution. Another closely related study is the one conducted by Gorry, Gorry and Trachter (2019), who explore the occupational changes of high school graduates in the NLSY79, a research question similar to this study. However, the two studies have different focuses: This current study focuses on the effects of the strength of a worker's comparative advantage on her occupational changes, while the previous work focuses on the effects of initial beliefs on future occupational changes.

[1]One could also study the effects of learning from a firm's perspective. For example, see Farber and Gibbons (1996); Altonji and Pierret (2001); Lange (2007) and Kahn (2013).

This study also adds to the broad literature on life-cycle wage growth and the dynamics of job change. Learning and the accumulation of heterogeneous human capital are two primary forces driving job change and wage growth (see Rubinstein and Weiss (2006) and Sanders and Taber (2012) for comprehensive reviews). Sanders (2010) compares the effects of learning and human capital accumulation on both job mobility and wage growth, finding that learning plays a primary role in job mobility but a minor role in wage growth. In line with his finding, this paper focuses on the effects of learning on occupational change.

1.2 Data Overview

1.2.1 Data Set

This study uses a subsample of high school graduates from the cross-sectional sample of the National Longitudinal Survey of Youth 1979 (NLSY79), which follows the lives of American youth born between 1957 and 1964. It is a rich data set measuring workers' abilities and tracking their career outcomes, features making it an excellent source for studying the effects of a worker's ability distribution on her occupational transitions. The survey, begun in 1979, was conducted annually until 1994 and biennially thereafter. In this paper, I use annual job observations between 1979 and 1994 when annual observations are available.[2]

Table 1.1 describes the sample construction process. The final sample contains 1,151 individuals and 11,770 annual job observations. Individuals in my sample received a high school diploma or a General Educational Development certificate (GED) as their highest degree when they were 17–19 years old. This study restricts job ob-

[2]Annual job observations are current or most recent jobs as of the interview date. The NLSY79 define them as CPS jobs.

servations to those in the first ten years of a career because occupational shopping is more prominent in these early years. For this study, a worker's career begins when she starts to work consecutively for two years. Workers who have their final degree before 1978 were excluded because the years when they start their careers are not available in the data. I also drop workers who did not start their careers in the two years after graduation so that workers in my sample have relatively homogeneous knowledge about occupations. Finally, to be included in this study, workers need to have had at least seven valid job observations in their first ten years so that they were firmly attached to the labor market.[3]

1.2.2 Three Broad Occupations

This study groups jobs into three broad occupations: white-collar, pink-collar, and blue-collar occupations as was done in Lee and Wolpin (2006) and Papageorgiou (2014). Table 1.2 reports the corresponding 3-digit 1970 occupational codes for three occupations. White-collar workers includes managers, administrators, professionals, and technicians, while pink-collar workers are sales personnel, clerks, and service workers, and blue-collar workers include mechanics, operators, drivers, laborers, and farmers.

An occupational change is defined here as a change among the three broad occupations. As Neal (1999) argues, occupational codes in the NLSY79 contain errors, which may cause false identifications of occupational changes. To address this issue, I follow Guvenen et al. (2020)'s strategy of assigning the occupation that is most often observed in a job spell to that job, an approach that assumes that workers do not change broad occupations within a job spell. Using this strategy, I modify fewer

[3]Workers have at most 11 annual job observations in the first ten years because they begin with zero years of experience. A valid annual job observation requires a hourly wage between one and one thousand real dollars based 2014 monetary value and information about its occupation.

than 9% of annual job observations for their broad occupations.[4] In the final sample, 43.5% of jobs are blue collars, 46.5% pink collars and 10.0% white collars.[5]

1.2.3 Overall Patterns

High school graduates shop for occupations frequently when they are young. On average, 11.95% of high school graduates in my sample switch between the three occupations each year during the first ten years of their careers. This result is in line with the occupational mobility of young workers found by Papageorgiou (2014), who reports that 11% to 14% of white male high school graduates between 18 to 20 switch between three broad occupations in eight months.[6] Figure 1.1 plots the proportion of workers in my sample who change occupations each year after labor market entry. When workers enter the labor market, they are uncertain about their productivities across occupations and, thus, update their beliefs of productivities rapidly. According to Figure 1.1, 17.55% of workers change occupations in the first year. As workers try various occupations, they gain the knowledge about their occupation-specific abilities. As a result, experienced workers are less likely to revise their beliefs so much that they change occupations. Ten years after labor market entry, only 8.29% of workers change occupations in a year.

However, despite the prevalence of occupational shopping, young workers do not change occupations permanently. After trying different occupations, they may

[4] Table 14 lists ten three-digit occupations where most of the modifications occur. Among them, managers and administrators (n.e.c.) has the most modifications. n.e.c. means "not elsewhere classified." As the occupation title indicates, it is likely to be coded incorrectly.

[5] Table 15 compares the number of observations in three broad occupations before and after the modification. There are two percentage points fewer of annual job observations in white-collar occupations after the modification, potentially because young workers tend to misreport their occupations as white-collar occupations.

[6] Papageorgiou (2014) uses different occupational groups from this paper for his sample of white male high school graduates. His three groups are white-collar occupations, blue-collar occupations involving precision production and repairs, and blue-collar occupations involving operators and laborers.

return to prior ones. Table 1.3 reports the proportion of workers who change occupations in a specific year and then return to the ones which they just left within a certain period. On average, more than one-third of workers return to prior occupations within three years after the initial change. The probability of return, however, declines sharply the more time after the initial change. The longer a worker stays in other occupations, the lower the probability is that she returns to the previous occupation. In the first year after the initial change, 17.28% of workers return, while in the second year 10.90% of workers return, and in the third year, only 7.30% of workers return. Kambourov and Manovskii (2008) find similar patterns but slightly lower return mobility for prime-age male workers.

Although on average young workers shop for occupations frequently, not all of them change occupations often in their early careers. Table 1.4 reports the proportion of workers with different occupational mobility in the first ten years of their careers as well as the average number of years that workers spend in the labor market before they move to their last occupations. As this table shows, 46.05% of young workers never change occupations in the first ten years, while 14.94% of young workers change occupations at least three times. The latter exhibit every high occupational mobility as there are only three broad occupations in my analysis. Consistent with their high occupational mobility, on average they spend 7.83 years to move into their last occupations in the first ten years of their careers.

1.3 A Learning Model of Occupational Choices

Motivated by the overall patterns of occupational shopping presented in Section 1.2.3, I develop a learning model of occupational choices, in which workers learn their occupation-specific productivities and make occupational choices based on the beliefs of their comparative advantages. This model provides new insights into how a worker's productivity distribution affects her occupational changes.

1.3.1 Preference and Production

An infinitely lived risk-neutral worker i maximizes the present value of her lifetime wage, which is presented by

$$\sum_{t=0}^{\infty} \beta^t w_{it}. \tag{1.1}$$

The economy includes the blue, pink and white collar occupations, and there are no search frictions. Each period, worker i makes an occupational choice. If she works in occupation j at time t, her output is

$$x_{ijt} = a_{ij} + z_{ijt}, \tag{1.2}$$

where a_{ij} is the worker i's innate productivity (ability) in occupation j, and z_{ijt} is the noise in the output process in occupation j at time t. Productivities are occupation-specific in my model.[7] Workers do not accumulate occupation-specific human capital at work.[8] The productivity a_{ij} for occupation j, which is fixed over a worker's career, is drawn independently from a normal distribution $N(k_j, \theta_j)$ at birth. The vector of a worker's productivities in the three occupations defines her comparative advantage.

[7]My model does not incorporate general human capital for the simplicity. However, including it does not affect the implications of my model as long as it has equal productivities across occupations at any given time and is public information. See papers by Antonovics and Golan (2012) and Groes, Kircher and Manovskii (2015) for examples of learning models with occupation-specific returns to general human capital.

[8]Sanders (2010) finds that skill accumulation plays a minor role in occupational transitions compared to learning about abilities. For this reason, I abstract from the accumulation of occupation-specific human capital in my model. This simplification helps the model highlight the interaction between productivity distance, learning and occupational transitions.

The random component of the output z_{ijt} follows an occupation-specific normal distribution $N(0, \sigma_j)$, and the parameter σ_j measures the risk of an occupation, with a high value of σ_j indicating that the occupation is risky in the sense that a worker's output in that occupation exhibits large fluctuations over time.

1.3.2 Learning

Although a worker knows the distributions of output noises in the three occupations, she has limited knowledge about her occupation-specific productivities when she enters the labor market. Following Gorry, Gorry and Trachter (2019), I assume that a worker's prior knowledge is equivalent to the observation of α periods of output in each occupation.[9] Worker i's belief of her productivity in occupation j at labor market entry has the normal distribution

$$P_0(a_{ij}) \sim N(\bar{x}_{ij0}, \frac{\sigma_j^2}{\alpha}), \tag{1.3}$$

where $\bar{x}_{ij0}$ is the mean of α periods of worker i's prior output in occupation j at labor market entry ($t = 0$), and $\frac{\sigma_j^2}{\alpha}$ measures the precision of worker i's belief about her productivity in occupation j at the entry. The precision increases as $\frac{\sigma_j^2}{\alpha}$ decreases. A worker exhibits lower precision concerning her belief about her productivity in a risky occupation than in a safe occupation. It should be noted that in this model each worker has the same amount of knowledge for a given occupation in the model.

After a worker enters the labor market, she learns about her productivity in her current occupation by observing the corresponding output at the end of each period. Given the normality of the belief at the entry and the noise in the output

[9] I assume that workers have an improper uniform prior at birth. It and the normal distributed noise ensure that the belief always has a normal distribution.

process, the prior belief for worker i in occupation j at time t is distributed normally as

$$P_t(a_{ij}) \sim N(\mu_{ijt}, \tau^2_{ijt}), \tag{1.4}$$

where $\mu_{ijt} = \bar{x}_{ijt}$ and $\tau^2_{ijt} = \frac{\sigma_j^2}{T_{ijt}}$. $\bar{x}_{ijt}$ is the mean of worker i's prior output in occupation j before time t, and T_{ijt} is worker i's accumulated tenure in occupation j before time t. Both $\bar{x}_{ijt}$ and T_{ijt} include α periods of equivalent output prior to labor market entry.

If worker i chooses occupation j at time t, then in the next period, the accumulated occupational tenure in occupation j increases by one period, represented by

$$T_{ijt+1} = T_{ijt} + 1, \tag{1.5}$$

and the accumulated tenure in the other two occupations does not change, represented by

$$T_{ij't+1} = T_{ij't}. \tag{1.6}$$

After worker i observes the output x_{ijt}, she updates the mean of her belief in occupation j as

$$\begin{aligned}
\mu_{ijt+1} &= \frac{\tau^2_{ijt}}{\tau^2_{ijt} + \sigma^2_j} x_{ijt} + \frac{\sigma^2_j}{\tau^2_{ijt} + \sigma^2_j} \mu_{ijt} \\
&= \frac{\sigma^2_j / T_{ijt}}{\sigma^2_j / T_{ijt} + \sigma^2_j} x_{ijt} + \frac{\sigma^2_j}{\sigma^2_j / T_{ijt} + \sigma^2_j} \bar{x}_{ijt} \\
&= \frac{x_{ijt} + \bar{x}_{ijt} \times T_{ijt}}{T_{ijt} + 1} \\
&= \frac{x_{ijt} + \bar{x}_{ijt} \times T_{ijt}}{T_{ijt+1}} \\
&= \bar{x}_{ijt+1},
\end{aligned} \tag{1.7}$$

and updates the variance of her belief as

$$\begin{aligned}\tau^2_{ijt+1} &= (\frac{1}{\tau^2_{ijt}} + \frac{1}{\sigma^2_j})^{-1} \\ &= (\frac{1}{\sigma^2_j / T_{ijt}} + \frac{1}{\sigma^2_j})^{-1} \\ &= \frac{\sigma^2_j}{T_{ijt}+1} = \frac{\sigma^2_j}{T_{ijt+1}}.\end{aligned} \tag{1.8}$$

Worker i's beliefs about her productivities in the other two occupations do not change at time t because she does not observe her output in occupations where she has not worked.

1.3.3 Wages

Firms are risk-neutral, have zero costs of entry, offer jobs in all occupations, and share the same information as workers. In this environment, any wage policy which provides the expected wage equal to the expected output is consistent with the equilibrium in Jovanovic (1979). I assume that wages in my model satisfy

$$w_{ijt} = 0.5\bar{x}_{ijt} + 0.5x_{ijt}. \tag{1.9}$$

Firms and workers share the uncertainty in the output process according to my wage contract.[10] This share of uncertainty does not change workers' learning process and, thus, their occupational transitions. The assumption that workers and firms are risk-neutral assures that only expected values matter in the decision process.

[10] There are other ways to assign uncertainty in the literature. For example, workers bear all the uncertainty if firms pay workers their realized output. Another extreme case is that firms bear all the uncertainty if firms pay workers their expected output. Groes, Kircher and Manovskii (2015) use both approaches in their paper. Here, I take the middle ground. The later calibration result shows that my wage contract is consistent with the data.

1.3.4 The Value Function

In this study, $\bar{\mathbf{x}}_{it}, \mathbf{T}_{it}$ are state variables for worker i at time t. $\bar{\mathbf{x}}_{it}$ is the vector of means of prior output in the three occupations, and $\mathbf{T}_{it}$ is the vector of accumulated occupational tenure in the three occupations before time t. $V(\bar{\mathbf{x}}_{it}, \mathbf{T}_{it})$ is the value function, which satisfies

$$V(\bar{\mathbf{x}}_{it}, \mathbf{T}_{it}) = \max\Big\{v_1(\bar{\mathbf{x}}_{it}, \mathbf{T}_{it}), v_2(\bar{\mathbf{x}}_{it}, \mathbf{T}_{it}), v_3(\bar{\mathbf{x}}_{it}, \mathbf{T}_{it})\Big\}, \tag{1.10}$$

where $v_j(\bar{\mathbf{x}}_{it}, \mathbf{T}_{it})$ is the value function of working in occupation j at time t, which is represented as

$$v_j(\bar{\mathbf{x}}_{it}, \mathbf{T}_{it}) = E\big(w_{ijt} \,|\, P_t(a_{ij})\big) + \beta E\big(V(\bar{\mathbf{x}}_{it+1}, \mathbf{T}_{it+1}) \,|\, P_t(a_{ij})\big). \tag{1.11}$$

The first element on the right in Equation 1.11 is the expected wage that worker i earns if she currently works in occupation j. It equals the expected output $E(x_{ijt})$. The second half is the discounted expected value at the next period if worker i chooses occupation j at time t.

For a worker whose prior belief is $P_t(a_{ij})$, according to the Bayes rule, her perceived probability density of producing x_{ijt} in the current period is

$$
\begin{aligned}
& f(x_{ijt}|P(a_{ij}|t)) \\
&\quad = \int_{-\infty}^{\infty} f(x_{ijt}|a_{ij}) \times g_t(a_{ij}) \mathrm{d}a_{ij} \\
&\quad = \int_{-\infty}^{\infty} (2\pi\sigma_j^2)^{-1/2} \exp\Big[-\frac{1}{2}(\frac{x_{ijt}-a_{ij}}{\sigma_j})^2\Big] \times (2\pi\tau_{ijt}^2)^{-1/2} \exp\Big[-\frac{1}{2}(\frac{\mu_{ijt}-a_{ij}}{\tau_{ijt}})^2\Big] \mathrm{d}a_{ij} \\
&\quad = \int_{-\infty}^{\infty} (2\pi\sigma_j^2)^{-1/2} \exp\Big[-\frac{1}{2}(\frac{x_{ijt}-a_{ij}}{\sigma_j})^2\Big] \times \big(2\pi\frac{\sigma_j^2}{T_{ijt}}\big)^{-1/2} \exp\Big[-\frac{1}{2}(\frac{\mu_{ijt}-a_{ij}}{\sigma_j/T_{ijt}})^2\Big] \mathrm{d}a_{ij} \\
&\quad = \big(2\pi\frac{\sigma_j^2 T_{ijt}}{T_{ijt+1}}\big)^{-1/2} \exp\Big[-\frac{1}{2}(\frac{x_{ijt}-\bar{x}_{ijt}}{\sigma_j\sqrt{T_{ijt}/T_{ijt+1}}})^2\Big] \\
&\quad = \phi\big(x_{ijt} \,\big|\, \bar{x}_{ijt}, \frac{\sigma_j^2 T_{ijt}}{T_{ijt+1}}\big),
\end{aligned}
\tag{1.12}
$$

where $g_t(a_{ij})$ is the p.d.f. of $P_t(a_{ij})$, and $\phi(\cdot)$ represents a normal density. Knowing that the perceived probability density follows a normal distribution with mean $\bar{x}_{ijt}$ and variance $\sigma_j^2 T_{ijt}/T_{ijt+1}$, we write Equation 1.11 as

$$
v_j(\bar{\mathbf{x}}_{it}, \mathbf{T}_{it}) = \bar{x}_{ijt} + \beta \int_{-\infty}^{\infty} V(\bar{\mathbf{x}}_{it+1}, \mathbf{T}_{it+1}) \phi\big(x_{ijt} \,\big|\, \bar{x}_{ijt}, \frac{\sigma_j^2 T_{ijt}}{T_{ijt+1}}\big) \mathrm{d}x_{ijt}. \tag{1.13}
$$

Theoretically, the dynamic problem defined by Equation 1.10 and Equation 1.13 could be solved using value function iterations. However, it becomes computationally burdensome as my model has three occupations and six state variables.

1.3.5 The Optimal Policy

In the model, a worker's beliefs concerning her productivities in the three occupations evolve independently and only when she works in the corresponding occupation. The optimal occupational choice here is a multi-armed bandit problem. Gittins (1979) proposes a method using indices to find an optimal policy. By assigning Gittins Indices to each occupation at different states, the optimal policy is always to choose the occupation with the highest index.

Gittins Indices transform the three-dimensional dynamic problem defined by Equation 1.10 and Equation 1.13 into three one-dimensional problems. Instead of considering the state spaces of three occupations, the Gittins Index of an occupation only depends on its state. Gittins Indices dramatically reduce the computational expnese and potentially allow my model to incorporate more than three occupations.[11]

Gittins Indices are computed using an outside option with a constant reward to evaluate a complicated bandit process, which, in my model, is whether to work in occupation j. Suppose an infinitely lived worker i faces two choices in each period: one is to work in occupation j with expected wage $E(w_{ijt}) = \bar{x}_{ijt}$, the other is to accept an outside option with a constant reward B. Once the worker chooses the outside option, she does not change because there is no new information about occupation j, and the outside option is always the best choice thereafter. The Gittins Index of occupation j is defined as the $B^\star$ which makes worker i indifferent between choosing the outside option and beginning with occupation j. This problem can be represented by the Bellman equation

$$R(B, \bar{x}_{ijt}, T_{ijt}) = \max\Big[\frac{B}{1-\beta}, \bar{x}_{ijt} + \beta \int_{-\infty}^{\infty} R(B, \bar{x}_{ijt+1}, T_{ijt+1}) \phi\big(x_{ijt} \,\big|\, \bar{x}_{ijt}, \frac{\sigma_j^2 T_{ijt}}{T_{ijt+1}}\big) \mathrm{d}x_{ijt}\Big], \tag{1.14}$$

where the Gittins Index $\nu(\bar{x}_{ijt}, T_{ijt}|\sigma_j^2, \beta)$ is the value of B for which the two expressions inside the square brackets are equal. Gittins Indices can be computed using backward induction.[12] As σ_j and β are parameters of the economy and do not change across workers, I omit them in the Gittins Index hereafter to simplify the notation.

[11] There is a caveat for using this method. Gittins Indices cannot be used when changing occupations is not costless.(Banks and Sundaram, 1994).

[12] Gittins, Glazebrook and Weber (2011) outline computational methods for normal reward processes in chapter 8.2 of their book.

We can decompose the Gittins Index into two parts as seen in Equation 1.15.[13]

$$\nu(\bar{x}_{ijt}, T_{ijt}) = \bar{x}_{ijt} + \sigma_j \nu_0(T_{ijt}). \tag{1.15}$$

The first part, $\bar{x}_{ijt}$, is the value of exploitation. It is the expected wage in occupation j at time t, which equals the expected output in the model. A worker i exploits occupation j in the sense that she keeps working in that occupation. The second part, $\sigma_j \nu_0(T_{ijt})$, is the value of exploration, which is the learning component of the Gittin Index.[14] It consists of two elements: the standard deviation of the noise in the output process σ_j, and the standardized Gittins Index $\nu_0(T_{ijt})$.[15] $\nu_0(T_{ijt})$ decreases with occupation-specific tenure T_{ijt} and goes to 0 when worker i keeps working in occupation j because a new observation of output adds little to the knowledge about the ability of an experienced worker. I will discuss more about the learning component in Section 1.7.2.

Gittins Indices summarize the optimal choices of young workers. A worker trades the value of exploitation with the value of learning when she chooses an occupation. There are two general rules. First, if a worker has the same mean of prior output in two occupations, she would choose the one with noisier output or shorter tenure so that she learns more about her abilities. It implies that workers start with risky occupations and move to safe occupations later. Second, if a worker has the same value of learning, she would choose the occupation with a larger expected output because such an occupation provides a higher expected wage.

[13] See Theorem 7.13 in Gittins, Glazebrook and Weber (2011).

[14] March (1991) first introduces the terminology of exploitation and exploration in the context of organizational learning.

[15] The standardized Gittins Index $\nu_0(T_{ijt})$ is the Gittins Index of which the expected wage is 0, the standard deviation of the noise is 1.

1.4 The Strength of a Worker's Comparative Advantage

Guided by the model, this section explores how the strength of a worker's comparative advantage, which is measured by the average distance between the estimated productivities in the best-matched occupation and the other two occupations, affects her occupational choices in her early career using the NLSY79.

1.4.1 Measurement

A worker's comparative advantage depends on her productivity in each of the three occupations. A larger average distance between the productivity in the best-matched occupation and the other two corresponds to a stronger comparative advantage, indicating that workers can more easily distinguish their best-matched occupation from the other two. Ideally, the average distance can be calculated using the equation below,

$$\begin{aligned} D_i &= 0.5 \times (A_{i,best} - A_{i,second}) + 0.5 \times (A_{i,best} - A_{i,third}) \\ &= A_{i,best} - 0.5 \times (A_{i,second} + A_{i,third}), \end{aligned} \tag{1.16}$$

where $A_{i,best}$ is the productivity in the best-matched occupation, and $A_{i,second}$, $A_{i,third}$ are the productivities in the other two occupations.

However, since we do not observe a worker's productivities directly in the data, as an alternative, I use the estimated indirect utility from a multinomial logit regression of choosing the best-matched occupation. From the estimation, I assume that workers have learned their comparative advantages and are working in their best-matched occupations after ten years of working experience. At that time, the average occupational mobility has decreased dramatically from 17.55% at labor market entry to 8.29%. My calibrated model also suggests that approximately 90% of workers find their best-matched occupations after ten years of working experience. Therefore, I use a worker's occupation at the end of her first ten years of her career as her best-matched one.

Worker i's utility of working in her best-matched occupation j is

$$U_{ij} = \mathbf{X}_i' \boldsymbol{\beta}_j + \epsilon_{ij}, \quad j = 1, 2, 3. \tag{1.17}$$

Occupation 1, 2, and 3 are blue-collar, pink-collar, and white-collar occupations. ϵ_{i1}, ϵ_{i2}, and ϵ_{i3} are independent and identically distributed with Gumbel distributions. $\mathbf{X}_i$ includes worker i's pre-market abilities, gender, race, and parental education level. This study uses cognitive ability, mechanical ability, and social ability to measure a worker's abilities, these measurements being carefully selected so that a worker's occupational choices do not affect them. Following past studies (e.g., Neal and Johnson, 1996; Heckman, Stixrud and Urzua, 2006), I use the Armed Forces Qualifications Test score (AFQT) to measure a worker's cognitive ability. The AFQT score is a composite score of mathematical knowledge, arithmetic reasoning, word knowledge, and paragraph comprehension, the four subtests in the Armed Services Vocational Aptitude Battery (ASVAB) measured in 1980 and 1981. I use normalized scores within three-month age groups provided by the NLS program staff to control for age effects.[16] Following Bacon (2017), I measure mechanical ability using the composite score of three subtests in the ASVAB: mechanical comprehension, auto and shop information, and electronic information. To be consistent with cognitive ability, I normalize me-

[16] Please refer to the NLSY79 website for details. `https://www.nlsinfo.org/content/cohorts/nlsy79/topical-guide/education/aptitude-achievement-intelligence-scores`

chanical ability within three-month age groups to control for age effects as well.[17] Social ability is measured by a worker's sociability at age 6 and is also normalized within three-month age groups.[18] Although other measurements of social ability are found in the literature (e.g., Borghans, Weel and Weinberg, 2014; Deming, 2017), my primary results are robust to these various measurements, and I use this measure to allow for a straightforward interpretation. Finally, I convert the normalized scores of three abilities into percentile scores ranging from 0 to 1.

Table 1.5 summarizes worker characteristics by their best-matched occupations. On average, workers who excel at white-collar jobs have the highest cognitive ability and social ability, while workers who are best suited for blue-collar jobs exhibit the highest mechanical ability. Regarding gender, blue-collar jobs are male-dominated, pink-collar jobs are female-dominated, and white-collar jobs are equally divided between male and female workers. In addition, workers who excel at blue-collar occupations are more likely to have fathers in the lowest education level compared to the other two occupations.

A worker i's probability of choosing occupation j as her best-matched occupation is represented as

$$\text{Prob[choosing occ. } j] = \frac{\exp(\mathbf{X}_i'\boldsymbol{\beta}_j)}{\exp(\mathbf{X}_i'\boldsymbol{\beta}_1) + \exp(\mathbf{X}_i'\boldsymbol{\beta}_2) + \exp(\mathbf{X}_i'\boldsymbol{\beta}_3)}. \tag{1.18}$$

Table 1.6 reports the coefficients of the multinomial logit estimation of Equation 1.18, where the white-collar occupation is the base choice. To better understand the effects of a worker's characteristics on the choice of her best-matched occupation, I also report the average marginal effects in Table 1.7. Consistent with evidence from the

[17]I use ASVAB sampling weights provided by the NLSY79 to normalize mechanical ability.

[18]In 1985, the NLSY79 asks the respondent's perception of how shy or outgoing they were at age 6. There are four scales: 1 extremely shy, 2 somewhat shy, 3 somewhat outgoing and 4 extremely outgoing. I normalize social ability using sample weights in 1985.

summary statistics in Table 1.5, young workers with lower cognitive abilities but higher mechanical abilities are more likely to work in blue-collar occupations. On the other hand, young workers with higher cognitive abilities but lower mechanical abilities are more likely to work in pink-collar occupations, and workers with higher cognitive abilities are more likely to work in white-collar occupations. In addition to abilities, female workers are less likely to work in blue-collar occupations but more likely to work in pink-collar occupations; however, gender does not have a significant effect on the probability of working in white-collar occupations. Regarding parental education, fathers' education plays an import role in children's occupational choices, but mothers' education has little effect. Workers whose fathers have lower education levels are more likely to work in blue-collar occupation but less likely to work in pink-collar occupations.

The predicted occupation-specific ability is

$$\hat{A}_{ij} = \hat{U}_{ij} = \mathbf{X}_i \hat{\boldsymbol{\beta}}_j, \tag{1.19}$$

where $\hat{\boldsymbol{\beta}}_j$ are coefficients of the multinomial logit regression seen in Table 1.6. Since the white-collar occupation is the base choice in the regression, the predicted productivity in the white-collar occupation $\hat{A}_{i3}$ equals zero for all workers. Moreover, the predicted productivities in the blue-collar occupation $\hat{A}_{i1}$ and the pink-collar occupation $\hat{A}_{i2}$ are relative values to the productivity in the white-collar occupation $\hat{A}_{i3}$. The first two rows of Table 1.8 summarize the predicted productivities. Most workers exhibit comparative advantages in either blue-collar or pink-collar occupations, but a few workers appear best-suited for white-collar occupations. These patterns are also seen in Figure 1.2a, which plots the distribution of workers with different productivities. The third row of Table 1.8 reports the predicted productivity in the best-matched occupation. Its mean and median are higher than the mean and median of each occupation's productivity, suggesting that workers are sorted into occupations with higher productivity in their early careers.

The estimated distance is represented by the following equation

$$\begin{aligned}\hat{D}_i &= 0.5 \times (\hat{A}_{i,best} - \hat{A}_{i,second}) + 0.5 \times (\hat{A}_{i,best} - \hat{A}_{i,third}) \\ &= \hat{A}_{i,best} - 0.5 \times (\hat{A}_{i,second} + \hat{A}_{i,third}).\end{aligned} \tag{1.20}$$

The last row of Table 1.8 summarizes the average distances between the productivities in the best-matched occupation and the other two occupations. The mean distance is 1.02 with a standard deviation of 1.15. The distance measure is normalized in later regressions to allow for the comparison of the results in the data with those in the simulated model. Figure 1.2b plots the distribution of the normalized average distance between productivities.

1.4.2 Effects on Occupational Shopping

This section focuses on the effects of the strength of a worker's comparative advantage on her occupational shopping. More specifically, it analyzes how this strength impacts the years that a worker spends in the labor market and the number of occupations that she tries out before discovering her best-matched one. A worker with a stronger comparative advantage exhibits more productivity in her best-matched occupation compared to her productivities in the other two. This worker is less likely to choose these two occupations rather than the best-matched one when she is uncertain about her comparative advantage. In the following analysis, a worker's last occupation at the end of her first ten years of her career is used as her best-matched one. We expect that there is a negative relationship between the strength and both years of labor market experience and the number of occupations before the best-matched one.

High school graduates in my sample on average spend 3.08 years in the labor market and try 1.09 occupations before moving to their best-matched one. However, workers take different paths to their best-matched occupations, with 46.05% finding their best-matched ones on the first try. The others on average spend 5.87 years and take 2.04 occupations before they move to their best-matched one. Given the large proportion of workers who do not change occupations in their early careers, I use negative binomial regressions rather than Poisson regressions to explore the effects of the strength of a worker's comparative advantage on occupational shopping.[19]

Table 1.9 reports the results of the negative binomial regression of years that a worker spends in the labor market before she moves to her best-matched occupation. To account for the possibility that the effect of the strength comes from the variables used before to predict occupation-specific productivities, I control for the variables used in the specification in Table 1.6, specifically the three pre-market abilities, gender, race, and parental education levels. I also control for the survey year when a worker enters the labor market because the labor market condition at entry may affect a worker's career progress (Altonji, Kahn and Speer, 2015). In Table 1.9, the coefficients are in the left column, and the average marginal effects are in the right column. I bootstrap standard errors of both the coefficients in the left column and the average marginal effects in the right. This estimation suggests that the strength of a worker's comparative advantage has a negative and significant effect on the number of years that she spends in the labor market finding her best-matched occupation. On average, a standard deviation decrease in the strength costs a worker additional 1.09

[19]Various tests, such as the Lagrangian multiplier test and the likelihood ratio test, suggest that there is an over-dispersion problem in Poisson regressions.

years to find her best-matched one.[20] However, a worker's pre-market abilities do not have significant effects on her time spent in the labor market to find her best-matched occupation, suggesting that the effect of a worker's strength of her comparative advantage comes from the distribution of a worker's productivities across occupations, not from the levels of a worker's innate abilities.

Table 1.10, which includes the same control variables in Table 1.9, reports the results of the negative binomial regression of the number of occupations a worker tries before moving to her best-matched one. Similar to the results in the preceding estimation, the strength of a worker's comparative advantage has a negative and significant effect on the number of occupations that she explores. On average, a standard deviation decrease in the strength increases the number of occupations by 0.32. In addition, a worker's pre-market abilities also do not have significant effects, further suggesting that levels of abilities are not the driving force for the occupational shopping of young workers.

1.5 Model Calibration

This section describes the approach used here to calibrate the parameters of the model, specifically the monthly discount factor β, the number of months of learning before starting work α, the standard deviations of noises in the output processes of the three occupations $(\sigma_1, \sigma_2, \sigma_3)$, and the distributions of workers' productivities in the three occupations, characterized by the distribution means (k_1, k_2, k_3) and standard deviations $(\theta_1, \theta_2, \theta_3)$. After calibrating the parameters, we can generate simulated data from the model.

[20] The measurement of the strength of a worker's comparative advantage is standardized to a mean of zero and a stand deviation of one. A one standard deviation decrease is equivalent to a decrease of one unit in the strength in this estimation and the next one.

First, the monthly discount factor β is set to 0.997, which is equivalent to an annual interest rate of 3.67%. Then, the remaining parameters are calibrated by simultaneously matching moments in the simulated data to targeted moments in the NLSY79. Although the simulated moments are affected by all parameters, I highlight the close relationship between some of them and their corresponding moments. First, the number of months of learning before starting work α, which measures the amount of workers' knowledge about their types (productivities) before they enter the labor market, is closely related to the proportion of workers who change occupations in the first year. Workers who know their types well at entry are not likely to revise their beliefs about their productivity in their current occupation to the extent that they change occupations in the first year. Second, according to the model, the wage growth of a worker who stays in one occupation is driven by the new information about her productivity revealed in the output process. The noise in the output process determines the amount of information that a worker learns about her type. Thus, the standard deviations of changes in log wages in the three occupations for workers not changing occupations in the first or second year are used to calibrate the standard deviations of three noises $(\sigma_1, \sigma_2, \sigma_3)$. The remaining parameters (k_1, k_2, k_3) and $(\theta_1, \theta_2, \theta_3)$, which describe the distributions of productivities in the three occupations, are calibrated by targeting the medians and standard deviations of the log wages in as well as the employment shares of these occupations in the first two years.

A worker's occupation-specific productivity is the underlying parameter that governs the mean of her previous output $\bar{x}_{ijt}$, which partially determines her wage and her Gittins Index. Therefore, the distributions of log wages in the three occupations are closely associated with the distributions of productivities. Also, since workers in the model choose their occupations by comparing the Gittins Indices of the three occupations, the employment shares are also highly correlated with occupation-specific productivities too. Only the moments in the first two years are used here to calibrate the model rather than a longer period because these early moments are less affected by factors other than learning. In addition, using these moments helps reduce the computational expense of the calibration by simulating shorter career paths.

To obtain the parameters, I minimize the mean of the squared percentage deviations of the simulated moments from the targeted moments in the data. As Table 1.12a, which displays these moments and their values in both the data and the calibrated model, shows, the mean of squared percentage deviations is 0.000639, suggesting that the simulated moments are close to their corresponding moments in the data.

Table 1.12b summarizes the parameters of the model along with their values. The calibrated number of months of learning before starting work α is 7.66, a value equivalent to 23 months of working experience during which a worker spends equal time in the three occupations. The amount of prior information is consistent with that found by Gorry, Gorry and Trachter (2019) in their results. Their calibrated number of months is 11.49, which is also equivalent to 23 months of working experience, for a model with only two occupations. The calibrated standard deviations of noises in the blue-collar, pink-collar and white-collar occupations are 5.49, 5.35 and 3.69 respectively, suggesting that the white-collar occupation is safer than blue-collar and pink-collar occupations in terms of the fluctuations in the output process. The last set of parameters include the means and standard deviations of worker productivity in the three occupations. The calibrated means in blue-collar, pink-collar, and white-collar occupations are 8.56, 9.32 and 4.48, respectively, with standard deviations of 3.42, 2.19 and 3.41. The calibrated means of the productivities suggest that high school graduates on average have higher productivities in blue-collar and pink-collar occupations than in white-collar occupations.

1.6 Baseline Results

This section presents results from the simulated model, beginning with the patterns of occupational shopping in the simulated model and their comparison with patterns in the data. Second, the effects of the strength of a worker's comparative advantage on her path to her best-matched occupation is analyzed and compared with the effects in the data.

1.6.1 Occupational Shopping

On average each year, 9.69% of the workers in the simulated model change occupations, while 11.95% of the workers in the data do. Figure 1.4 compares occupational mobility in the simulated model with that in the data. Consistent with the data, the simulated model generates declining mobility as workers become experienced. In the first year after entering the labor market, 17.4% of workers in the simulated model change occupations. After ten years of working experience, only 5% of workers change occupations in a year. Although the calibration only targets occupational mobility in the first year, the simulated mobility in the first four years fits the data pretty well. However, in later years, the simulated occupational mobility declines more rapidly than the mobility in the data. Occupational changes resulted from other reasons, including human capital accumulation and family considerations, potentially explaining why the occupational mobility in the data dose not decrease as quickly as that in the simulated model.

The simulated model also generates conditional return mobility. Approximately 55% of workers return to their previous occupations in the next three years. Table 1.13 reports the proportion of workers in the simulated model who return in the next few years if they change occupations in a particular year. Consistent with the data, workers in the simulated model also have a lower probability of returning to their previous occupations after they work in other occupations for a more extended period.

In addition, the simulated model generates a similar occupational transition matrix to the data. Table 1.14 compares the two matrices. Each cell reports the proportion of workers who are in occupation j (row) in the current year and then move to occupation j' (column) in the next year. Workers in both the data and the simulated model are more likely to change from white-collar occupations to blue-collar or pink-collar occupations rather than the reverse. This result suggests that the stepping-stone mechanism proposed by Jovanovic and Nyarko (1997) is not the primary one for explaining the occupational mobility discussed in this paper.[21] In addition to the asymmetry of off-diagonal elements, both transition matrices have similar on-diagonal elements, suggesting that the proportion of workers not changing occupations in a year from the simulated model is similar to the data.

Moreover, in the simulated model, 89.80% of workers are in their best-matched occupations after ten working years. For each worker, the best-matched occupation is the one with the highest productivity. The simulated result suggests that most of the workers have ascertained their comparative advantages by that time. Thus, it is reasonable to assume that the last occupation at the end of the first ten years of a worker's career is her best-matched one as suggested in Section 1.4.

[21]In general, blue-collar and pink-collar occupations are stepping stones for white-collar ones. If the step-stone mechanism is the primary driving force, we should observe a higher probability of changing from blue-collar or pink-collar occupations to white-collar occupations than the probability of changing from the reverse order. This pattern is not found either in the data or in the simulated model.McCall (1990) and Kambourov and Manovskii (2008) do not find much evidence of step-stone mechanism at one-digit occupational level either.

1.6.2 The Effects of the Strength of a Worker's Comparative Advantage

This section discusses how the strength of a worker's comparative advantage affects her path to her best-matched occupation using the simulated data. An advantage of the simulated data is the explicit measure of a worker's productivities in the three occupations, meaning we can observe the strength of a worker's comparative advantage directly in the simulated model.

Figure 1.5 compares workers' paths for finding their best-matched occupations in the data with paths in the simulated model. To be consistent with the data, the plots from the simulated model also use the last occupation at the end of the first ten years of a worker's career as her best-matched one. The simulated model replicates a large percentage of workers from the data who do not change occupations in their early careers. More specifically, 61.75% of the workers in the simulated model find their best-matched occupations on their first tries, as do 46.05% of the workers in the data. Such workers are omitted in Figure 1.5 to highlight the rest of the distributions. The top panel of Figure 1.5 reports the distributions of the number of years that workers spend in the labor market before they move to their best-matched occupations in both the data and the simulated model. On average, workers in the simulated model spend 2.017 years in the labor market, while workers in the data spend 3.094 years. In addition, the distributions in both the simulated model and the data are U-shaped. The bottom panel reports the distributions of the number of occupations that workers try before moving to their best-matched ones. On average, workers in the simulated model try 0.968 occupations before the best-matched one, while workers in the data try 1.097 occupations. Fewer workers in both the simulated model and the data try more occupations before they find their best-matched ones. However, only a small proportion of workers in the simulated model only change occupations once. Given that career paths are not directly targeted in the calibration, in general the simulated model generates distributions fairly consistent with the data.

Next, I study how the strength of a worker's comparative advantage affects her process of finding the best-matched occupations analogous to the analysis in Section 1.4. As we observe occupation-specific productivities, the strength of a worker's comparative advantage is measured using the productivities directly, which is

$$D_{i,simu} = 0.5 \times [(A_{i,last} - A_{i,other1}) + (A_{i,last} - A_{i,other2})]. \tag{1.21}$$

$A_{i,last}$ is a worker's last occupation's productivity at the end of her first ten years of her career, and $A_{i,other1}$ and $A_{i,other2}$ are productivities in the other two occupations. Based on the procedure detailed in Section 1.4, $D_{i,simu}$ is standardized to a mean of zero and a standard deviation of one to enable the comparison with results from the data. The negative binomial regressions for the simulated data also control productivities in the three occupations. Table 1.15 compares the average marginal effects in both the data and the simulated model. The results from the simulated model confirm the negative relationship between the strength of a worker's comparative advantage and both the number of years that she spends in the labor market and the number of occupations that she tries before the best-matched one. Moreover, the average marginal effects from the simulated model are larger than the effects from the data because the simulated model concentrates on the learning mechanism while workers in the NLSY79 have other reasons for occupational changes.

1.7 Experiments

The previous section shows that the calibrated model is able to quantitatively replicate primary patterns of occupational shopping in the NLSY79. This section uses the simulated model, quantifying the importance of the strength of a worker's comparative advantage on her occupational shopping and the value of learning.

1.7.1 The Importance of the Strength of a Worker's Comparative Advantage

In this section, I quantify the importance of the strength of a worker's comparative advantage on her occupational shopping by adjusting the strength of her comparative advantage in the model. In the following experiment, the strength of all workers' comparative advantages is increased by one standard deviation, which is equal to 2.57. The increase is approximately 75% of the difference in the strength between the third quartile and the first quartile. As the strength is measured by the average distance between the productivities in the best-matched occupation and the other two occupations in Equation 1.21, I enlarge the strength by increasing workers' productivities in their best-matched occupations by one standard deviation of the strength.[22]

Figure 1.6 reports the occupational mobility in the simulated model and in the counterfactual experiment. A standard deviation increase in the strength substantially reduces the occupational shopping. In the first year, the number of workers in the experiment who change occupations is reduced to one third of the number in the simulated model. After five years in the labor market, fewer than one percent

[22]Since only the distance matters when workers learn about their types and make occupational choices, the mobility generated by the experiment would be the same if I decrease the productivities in occupations other than the best-matched one by one standard deviation of the strength.

of workers change occupations each year. On average, increasing the strength by one standard deviation reduces occupational changes by 82% in the first ten years of workers' careers.

Figure 1.7 divides workers into two groups based on the relative strength of their comparative advantages. Panel 1.7a compares the occupational mobility of workers whose strength of their comparative advantages is higher than the median from the simulated model with the counterfactual experiment. Panel 1.7b reports the occupational mobility of workers whose strength is weaker than the median. As the strength of all workers' comparative advantages is increased by one standard deviation, their ranks are the same in the simulated model and in the counterfactual experiment. Despite of the difference in the comparative advantages in the simulated model, the experiment shows similar effects on the reduction in occupational changes for all workers.

1.7.2 Workers' Value of Learning Their Comparative Advantages

Based on Section 1.3.5, I use the difference between the present value of expected lifetime wages in an alternative occupation and a worker's choice of occupations in the simulated model to measure the worker's value of learning her comparative advantage (type). The alternative occupation is an occupation which offers a constant reward $B^{\star}$ equal to the worker's Gittins Index of her choice $\nu(\bar{x}_{ijt}, T_{ijt})$ in each period. According to the definition of Gittins Indices, the worker is indifferent between the alternative occupation and her choice of occupations in the simulated model if she has the option of learning. Therefore, the difference between the expected lifetime earnings in the two occupations provides a measurement of the value of learning, which is represented as

$$\begin{aligned}
\eta(\bar{x}_{ijt}, T_{ijt}) &= \frac{B^{\star}}{1-\beta} - \frac{E(w_{ijt})}{1-\beta} \\
&= \frac{\nu(\bar{x}_{ijt}, T_{ijt})}{1-\beta} - \frac{E(w_{ijt})}{1-\beta} \\
&= \frac{\bar{x}_{ijt} + \sigma_j \nu_0(T_{ijt})}{1-\beta} - \frac{\bar{x}_{ijt}}{1-\beta} \\
&= \frac{\sigma_j \nu_0(T_{ijt})}{1-\beta}.
\end{aligned} \tag{1.22}$$

From this equation, a worker's expected wage $E(w_{ijt})$ is equal to $\bar{x}_{ijt}$ according to her belief of her output in the next period, which is defined by Equation 1.12. In addition, $\nu_0(T_{ijt})$ is the standard Gittins Index defined in Section 1.3.5. It is worth noting that the numerator in Equation 1.22 is her learning component in the Gittins Index discussed by Gittins and Wang (1992).

To better understand the value of learning, I calculate the mean value of learning in terms of the mean expected lifetime wages, which is

$$\begin{aligned}
\eta\% &= \frac{\sum_i \sigma_j \nu_0(T_{ijt})/(1-\beta)}{N} / \frac{\sum_i (\bar{x}_{ijt})/(1-\beta)}{N} \\
&= \frac{\sum_i \sigma_j \nu_0(T_{ijt})}{\sum_i \bar{x}_{ijt}}
\end{aligned} \tag{1.23}$$

where N is the total number of workers, and j is the occupational choice for worker i in time period t. Figure 1.8 reports the relative mean value of learning ($\eta\%$) during workers' early careers. The value of learning decreases at a declining rate. For an average worker, the value of learning is 28% of her lifetime income. Given that the monthly discount rate is set to 0.997, the value of learning is equivalent to 93 months of the current expected wage for an average worker. After 10 years of working experience, 90% of workers in the simulated model are in their best-matched occupations, and the value learning decreases to 0.041% of an average worker's lifetime income, which is equivalent to 13.6 months of the current expected wage.

1.8 Conclusion

Both empirical results and the simulated model find that the strength of a worker's comparative advantage is an important factor explaining the occupational shopping of young workers. To measure the strength, this study uses the average distance between the productivities in the best-matched occupation and the other two occupations. Both in the data and the simulated model, workers with weaker comparative advantages are more likely to change occupations. These workers also spend more time in the labor market and try more occupations before finding their best-matched ones.

In addition, the model suggests that a one-standard-deviation increase in the strength of workers' comparative advantages leads to a reduction of more than 80% of the simulated occupational transitions in the first ten years. Moreover, for an average labor market entrant, the value of learning is approximately 28% of the present value of her expected lifetime earning.

Tables

Table 1.1: Sample Construction

Criteria	Remaining	
	Individuals	Annual Obs.
Cross sectional sample, between 1979–1994	6,111	91,073
Have a high school diploma or GED as the highest degree	2,974	43,887
Get a high school diploma or GED between ages 17–19	2,580	38,006
Get a high school diploma or GED in 1978 or later	1,822	27,053
Never work in the military	1,819	23,298
Valid CPS jobs	1,787	19,211
Start to work consec. for 2 years within 24 months after grad.	1,315	15,288
CPS jobs in the first 10 years	1,315	12,531
Have at least 7 jobs	1,151	11,770

Notes:

[1] GED represents General Education Development certification.

[2] This paper focuses on annual job observations in the first ten years of careers. Annual job observations are the current or most recent jobs as of the interview date. The NSLY79 defines them as CPS jobs.

[3] A valid annual job observation requires an hourly wage between one and one thousand real dollars in 2014 value and information about its occupation.

[4] The final sample contains 1,151 individuals and 11,770 annual job observations.

Table 1.2: Three Broad Occupations

Three Broad Occ.	One-digit Occupations	1970 Occ. Codes
White collar	Professional, technical workers, and kindred workers	$001 - 195$
White collar	Mangers and administrators, except farm-related workers	$201 - 254$
Pink collar	Sales workers	$260 - 285$
Pink collar	Clerical and unskilled workers	$301 - 395$
Pink collar	Service workers, except private household	$901 - 965$
Pink collar	Private household workers	$980 - 984$
Blue collar	Craftsmen and kindred workers	$401 - 579$
Blue collar	Operatives, except transport	$601 - 695$
Blue collar	Transport equipment operatives	$701 - 715$
Blue collar	Laborers, except farm-related workers	$740 - 785$
Blue collar	Farmers and farm managers	$801 - 802$
Blue collar	Farm laborers and farm foremen	$821 - 824$
Military	Former or current members of the Armed Forces	$580, 590$

Note:
[1] Workers who ever worked in the military are not in the final sample.

Table 1.3: Percentage of Workers Returning to Prior Occupations

Year After Labor Market Entry	Fraction of Workers Return in			Total % of Workers Return in 3 Years
	First Year	Second Year	Third Year	
1	18.32%	8.91%	7.43%	34.65%
2	22.73%	11.04%	8.44%	42.21%
3	14.73%	14.73%	7.75%	37.21%
4	14.05%	14.05%	6.61%	34.71%
5	15.11%	9.35%	8.63%	33.09%
6	18.97%	9.48%	6.03%	34.48%
7	19.82%	11.71%	5.41%	36.94%
8	13.33%	9.17%	—	—
9	17.02%	—	—	—
Average	17.28%	10.90%	7.30%	—

Notes:

[1] The table uses a subsample of high school graduates in the NLSY79, constructed by the researcher.

[2] The percentage in each cell is the percentage of workers who change occupations in the current year and then return to the occupation within a given period.

Table 1.4: The Distribution of Occupational Mobility

Number of Occupational Changes	Number of Workers	Proportion of Workers	Mean Years of LM Experience before the Last Occupation
0	530	46.05%	0
1	245	21.29%	4.28
2	204	17.72%	6.14
3+	172	14.94%	7.83

Notes:

[1] The sample is a subset of high school graduates in the NLSY79, constructed by the author in Table 1.1.

[2] Each row reports the number and percentage of workers with given mobility in the first ten years of their careers as well as the mean years of labor market experience before workers move to their last occupations.

Table 1.5: Summary Statistics of Workers' Characteristics

	Mean and Standard Deviation			
	Blue	Pink	White	All
Cognitive ability	0.4225	0.4623	0.5237	0.4526
	(0.2389)	(0.2326)	(0.225)	(0.2364)
Mechanical ability	0.5925	0.4053	0.5227	0.5014
	(0.2829)	(0.2327)	(0.2723)	(0.2748)
Social ability	0.4757	0.4808	0.4984	0.4808
	(0.2595)	(0.2732)	(0.2741)	(0.2672)
	Percentage			
	Blue	Pink	White	All
Female	16.27%	74.83%	50.41%	46.30%
Hispanic	3.54%	6.99%	10.74%	5.95%
Black	9.91%	8.39%	6.61%	8.83%
Father's education: less than HS	41.04%	31.24%	32.23%	35.63%
Father's education: more than HS	16.75%	21.45%	21.49%	19.40%
Mother's education: less than HS	33.96%	31.93%	29.75%	32.55%
Mother's education: more than HS	11.79%	11.89%	11.57%	11.81%
	Observation			
	Blue	Pink	White	All
Number of workers	424	429	121	974
Percentage of workers	43.53%	44.05%	12.42%	100%

Notes:

[1] The table uses a subsample of high school graduates from the NLSY79, constructed by the researcher. The 177 workers who miss information about three abilities, gender, race, parental education level are dropped in the table.

[2] I group workers by their occupations at the end of the first ten years of careers, assuming that final occupations are the best-matched ones.

[3] Cognitive ability, mechanical ability, and social ability are pre-market abilities. I use the AFQT score to measure cognitive ability. It is a composite score of mathematical knowledge, arithmetic reasoning, word knowledge, and paragraph comprehension, the four subtests in the ASVAB. Vast majority of workers took the ASVAB tests in 1980. I measure mechanical ability using three subtests in the ASVAB: mechanical comprehension, auto and shop information, and electronic information. Social ability is measured by the sociability at age 6, as asked in 1985. All three abilities are normalized within three-month age groups. I convert the normalized scores of three abilities into percentile scores, which range from 0 to 1.

Table 1.6: The Multinomial Logit Regression: Best-matched Occupations

	Blue-collar	Pink-collar
Cognitive Ability	-2.697^{***}	-0.736
	(0.635)	(0.611)
Mechanical Ability	1.348^{**}	-0.859
	(0.655)	(0.647)
Social Ability	-0.377	-0.141
	(0.412)	(0.393)
Female	-1.461^{***}	0.858^{***}
	(0.288)	(0.273)
Hispanic	-1.393^{***}	-0.597
	(0.451)	(0.389)
Black	0.009	-0.189
	(0.454)	(0.443)
Father's education: less than HS	0.447^{*}	-0.207
	(0.265)	(0.258)
Father's education: more than HS	-0.275	0.137
	(0.312)	(0.295)
Mother's education: less than HS	0.223	0.043
	(0.272)	(0.262)
Mother's education: more than HS	0.248	0.099
	(0.371)	(0.359)
Constant	2.302^{***}	1.629^{***}
	(0.472)	(0.463)
Observation	974	

Notes:
[1] The table reports the coefficients of the multinomial logit regression with standard errors in the parenthesis.
[2] The white-collar occupation is the base choice.
[3] Non-black and non-Hispanic male workers whose parents are both high school graduates are omitted in the table as they are the base group.
[4] $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table 1.7: Average Marginal Effects: Best-matched Occupations

	Blue-collar	Pink-collar	White-collar
Cognitive Ability	-0.358 ***	0.1875 **	0.1705 ***
	(0.0764)	(0.0779)	(0.0632)
Mechanical Ability	0.3234 ***	-0.3103 ***	-0.013
	(0.0751)	(0.0797)	(0.066)
Social Ability	-0.0455	0.0194	0.0261
	(0.0492)	(0.0501)	(0.0394)
Female	-0.4288 ***	0.4115 ***	0.0173
	(0.0382)	(0.0411)	(0.0307)
Hispanic	-0.164 ***	0.0346	0.1293 **
	(0.0587)	(0.0649)	(0.0649)
Black	0.0239	-0.0341	0.0102
	(0.0534)	(0.0567)	(0.0461)
Father's education: less than HS	0.0977 ***	-0.0878 ***	-0.0099
	(0.0306)	(0.0322)	(0.0241)
Father's education: more than HS	-0.0608	0.057	0.0037
	(0.0375)	(0.0397)	(0.0294)
Mother's education: less than HS	0.0317	-0.0187	-0.013
	(0.0333)	(0.0337)	(0.0248)
Mother's education: more than HS	0.029	-0.0118	-0.0172
	(0.0435)	(0.0476)	(0.0346)

Notes:

[1] The table reports the average marginal effects of the multinomial logit regression in Table 1.6 with bootstrapped standard errors in the parenthesis.

[2] Non-black and non-Hispanic male workers whose parents are both high school graduates are omitted in the table as they are the base group.

[3] $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table 1.8: Summary Statistics of Estimated Productivities

	Mean	S.D.	Min	25%	Median	75%	Max
Productivity in blue-collar occ.	1.03	1.16	-2.75	0.11	1.07	1.98	3.54
Productivity in pink-collar occ.	1.12	0.64	-0.51	0.57	1.09	1.69	2.54
Productivity in last-observed occ.	1.39	0.87	-1.36	0.78	1.57	1.99	3.54
Average distance (raw)	1.02	1.15	-2.25	-0.01	1.45	1.87	3.27

Notes:

[1] The average distance in the table is the average distance between the productivity in the best-matched occupation and in the other two. The average distance in the table is not normalized.

[2] The productivity in the white-collar occupations is zero since white-collar occupation is the base choice. Moreover, the productivities in blue-collar and pink-collar occupations are relative abilities to the ability in white-collar occupations.

Table 1.9: Negative Binomial Regression: Years before Moving to the Last Occ.

Variables	Coefficients	Average marginal effects
Average distance	-0.3507 ***	-1.0933 ***
	(0.0335)	(0.1037)
Cognitive ability	-0.1111	-0.3465
	(0.2266)	(0.7025)
Mechanical ability	-0.3176	-0.99
	(0.2402)	(0.7459)
Social ability	0.1466	0.4569
	(0.1552)	(0.4801)
Female	-0.1256	-0.3899
	(0.1011)	(0.3095)
Hispanic	0.1012	0.3306
	(0.1784)	(0.65)
Black	-0.0345	-0.1052
	(0.1595)	(0.4654)
Father's education: less than HS	0.1725 *	0.522 *
	(0.0957)	(0.291)
Father's education: more than HS	0.2498 **	0.7868 **
	(0.1198)	(0.391)
Mother's education: less than HS	-0.1216	-0.3655
	(0.1003)	(0.2949)
Mother's education: more than HS	0.1148	0.3885
	(0.1442)	(0.5001)
Constant	1.4064 ***	—
	(0.1968)	—
Year of entering the labor market	Yes	
Number of Observations	974	
Log Likelihood	-2089.495	
θ	0.476*** (0.033)	
Akaike Inf. Crit.	4216.989	

Notes:
[1] The table reports the bootstrapped standard errors both for the coefficients and the average marginal effects in the parenthesis.
[2] On average, workers take 3.08 years to move to the last-observed occupations.
[3] The base group are non-black and non-Hispanic male workers whose parents are both high school graduates.
[4] $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table 1.10: Negative Binomial Regression: the Number of Occ. before Moving to the Last One

Variables	Coefficients	Average marginal effects
Average distance	-0.2598 ***	-0.2856 ***
	(0.0314)	(0.0344)
Cognitive ability	0.003	0.0033
	(0.2186)	(0.2403)
Mechanical ability	-0.3383	-0.3719
	(0.2371)	(0.2608)
Social ability	0.1866	0.2052
	(0.1495)	(0.1635)
Female	-0.2967 ***	-0.3217 ***
	(0.1045)	(0.1123)
Hispanic	0.0539	0.0612
	(0.1626)	(0.1976)
Black	-0.0858	-0.0908
	(0.1533)	(0.1582)
Father's education: less than HS	0.0477	0.0514
	(0.0931)	(0.0999)
Father's education: more than HS	0.1227	0.1375
	(0.1099)	(0.1265)
Mother's education: less than HS	-0.0133	-0.0144
	(0.0955)	(0.1019)
Mother's education: more than HS	0.1189	0.1372
	(0.1327)	(0.1594)
Constant	0.4127 **	—
	(0.2001)	—
Year of entering the labor market	Yes	
Number of Observations	974	
Log Likelihood	-1368.723	
θ	1.995*** (0.318)	
Akaike Inf. Crit.	2775.446	

Notes:
[1] The table reports the bootstrapped standard errors both for the coefficients and the average marginal effects in the parenthesis.
[2] On average, workers experience 1.09 occupations before they move to their last-observed occupations.
[3] The base group are non-black and non-Hispanic male workers whose parents are both high school graduates.
[4] $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table 1.11: Moments and Parameters

(a) Summary of Moments

Moment		Data Target	Simulated Value
Proportion of workers changing occ. in the 1st year		0.1755	0.1742
S.D. of changes in log wages in the first year or second year for workers who do not change occupation in a year at	blue-collar	0.3878	0.3936
	pink-collar	0.4060	0.4161
	white-collar	0.2932	0.2901
Median of log wages in the first two years at	blue-collar	2.4013	2.4104
	pink-collar	2.2327	2.3398
	white-collar	2.3132	2.2978
S.D. of log wages in the first two years at	blue-collar	0.4086	0.3924
	pink-collar	0.3934	0.3741
	white-collar	0.3494	0.3295
Employment share in the first two years at	blue-collar	0.4205	0.4205
	pink-collar	0.5226	0.5229
	white-collar	0.0569	0.0566

(b) Summary of Parameters

Parameter	Value	Description	
β^*	0.9970	Monthly discount factor	
α	7.6641	Months of learning before starting work	
σ_1	5.4874	S.D. of the noise in the output process in	blue-collar
σ_2	5.3494		pink-collar
σ_3	3.6867		white-collar
k_1	8.5606	Mean of workers' productivities in	blue-collar
k_2	9.3241		pink-collar
k_3	4.4801		white-collar
θ_1	3.4217	S.D. of workers' productivities in	blue-collar
θ_2	2.1906		pink-collar
θ_3	3.4060		white-collar

Note:
* I set β equal to 0.9970 before the calibration. It is equivalent to an annual interest rate of 3.67%.

Table 1.13: Percentage of Workers Return to the Occupation That They Leave in the Current Year

Potential Experience	Percentage of workers return after			Percentage of workers return in three years
	one year	two years	three years	
1	37.25%	13.05%	6.27%	56.57%
2	37.74%	12.51%	6.25%	56.50%
3	37.03%	12.73%	6.36%	56.12%
4	35.73%	11.98%	5.78%	53.49%
5	36.68%	11.96%	6.38%	55.03%
6	35.54%	11.81%	6.38%	53.73%
7	35.78%	11.54%	5.89%	53.21%
8	35.02%	11.19%	—	46.27%
9	36.49%	—	—	—
Average	36.61%	12.29%	6.20%	—

Notes:
[1] The percentages are based on workers who change occupations in the current year.

Table 1.14: Occupational Transition Matrix

	Data			Simulated Model		
Occupation	Blue-collar	Pink-collar	White-collar	Blue-collar	Pink-collar	White-collar
Blue-collar	0.90	0.08	0.02	0.90	0.09	0.01
Pink-collar	0.08	0.88	0.04	0.07	0.92	0.02
White-collar	0.08	0.13	0.79	0.07	0.11	0.83

Note:
[1] The value in each cell represents the proportion of workers who are in occupation j (row) in the current year and then move to occupation j' (column) in the next year.

Table 1.15: Data v.s. Simulated Model: Average Marginal Effects of The Strength of A Worker's Comparative Advantage

Average Marginal Effects	Data	Simulated Model
Years before moving to the last occupation	-1.093*** (0.104) [3.094]	-3.246*** (0.041) [2.017]
Number of occupations before moving to the last occupation	-0.286*** (0.034) [1.097]	-1.295*** (0.016) [0.968]

Notes:

[1] The strength of a worker's comparative advantage is measured by the average distance between productivities in the best-matched occupation and the other two. In the data, each occupation's productivity is predicted by a multinomial logit regression of choosing the best-matched occupation as in Table 1.6. In the simulated model, the productivity is drawn independently from occupation-specific normal distributions calibrated in Section 1.5. I assume that the last occupation in the first ten years of a worker's career is her best-matched one.

[2] The average distances both in the data and in the simulated model are standardized with a mean of zero and a variance of one. The top value in each cell represents the average effect of an increase in the distance by one standard deviation for all workers.

[3] Standard errors are in parentheses. The results for the data use bootstrapped standard errors.

[4] Means of years and number of occupations before moving to the last occupation are in brackets.

[5] $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Figures

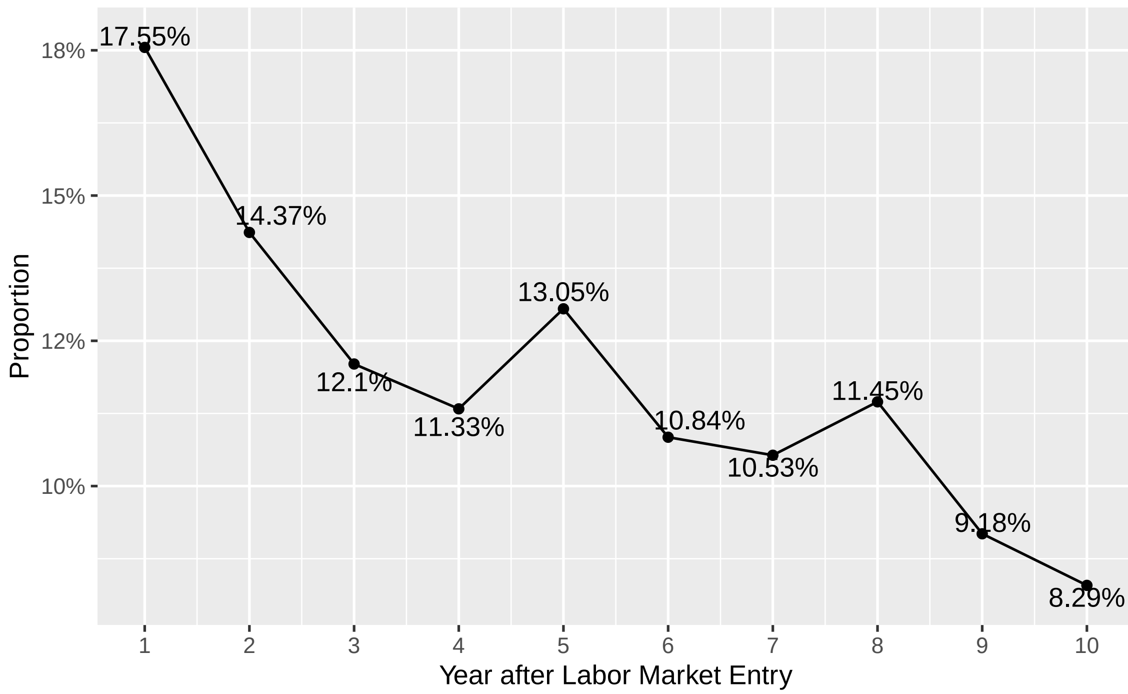
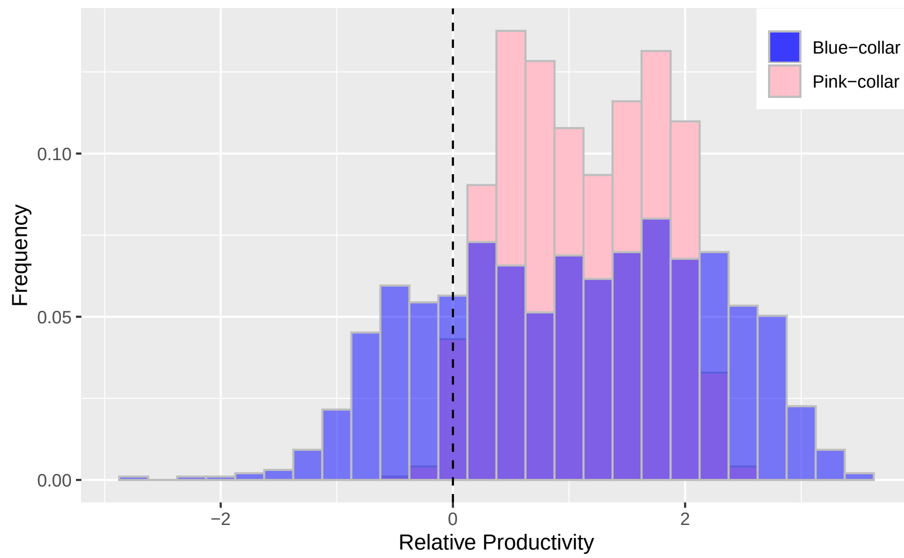
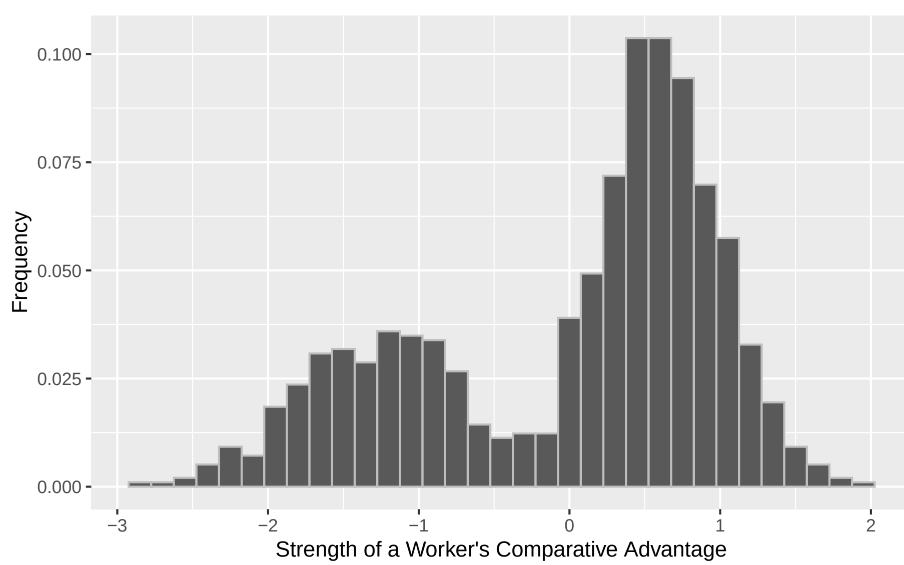


Figure 1.1: Proportion of Workers Who Change Occupations in a Year

Note: The figure plots the occupational mobility of 1151 high school graduates in the NLSY79, constructed by the author. In each survey year, a worker decides whether to change her occupation between blue-collar, pink-collar and white-collar occupations or not. On average, 11.95% of workers change occupations in a year.



(a) The Distribution of Productivities in Blue-Collar and White-Collar Occupations Relative to White-Collar Occupations



(b) The Distribution of the Strength of Workers' Comparative Advantage, Measured by the Average Distance between Productivities in the Best-matched Occupation and the Other Two (normalized)

Figure 1.2: Distributions of Estimated Productivities and the Strength of Workers' Comparative Advantage

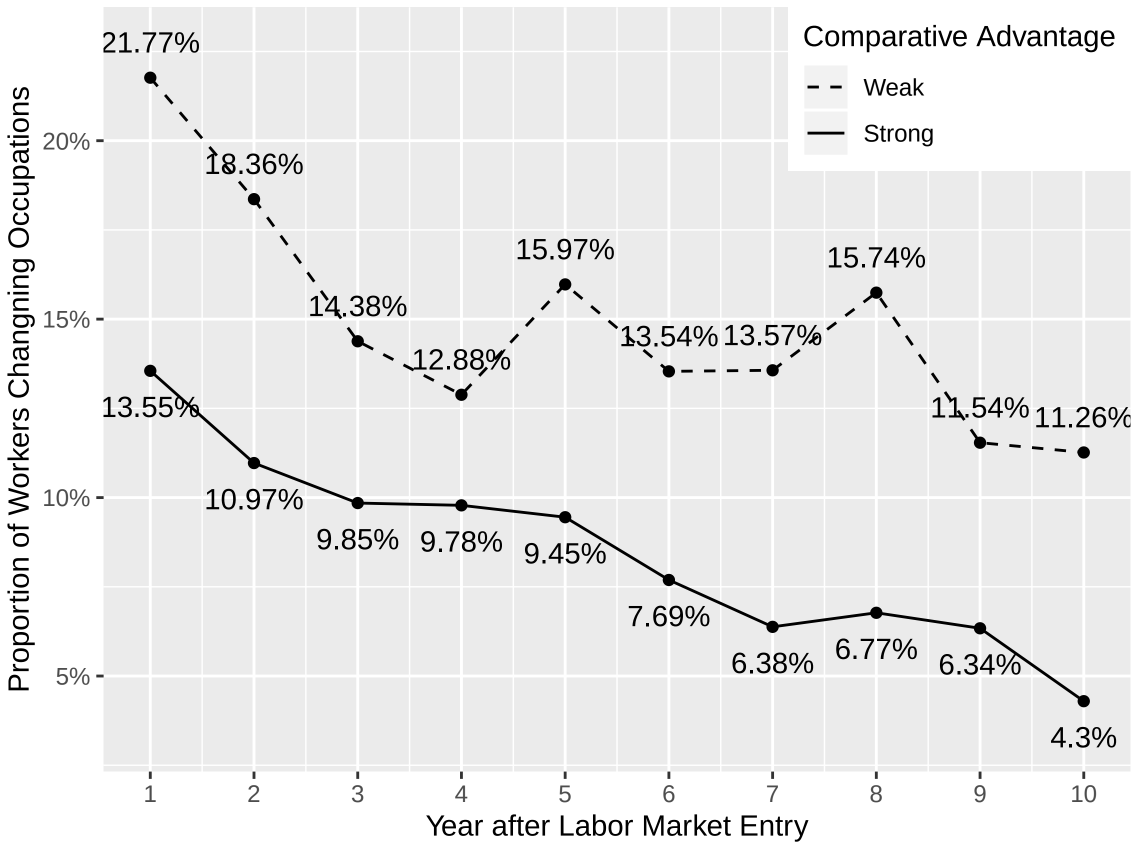


Figure 1.3: Occupational Mobility and The Strength of A Worker's Comparative Advantage

Notes: The sample contain 974 high school graduates in the NLSY79, constructed by the author. A worker has a weak comparative advantage if her average distance between the productivities in the best-matched occupation and in the other two is smaller than the median distance.Otherwise, she has a strong comparative advantage. I assume that the last occupation in the first ten years of a worker's career is her best-matched one. In each year, a worker who has a strong comparative advantage is less likely to change an occupation than her peer who has a weak comparative advantage.

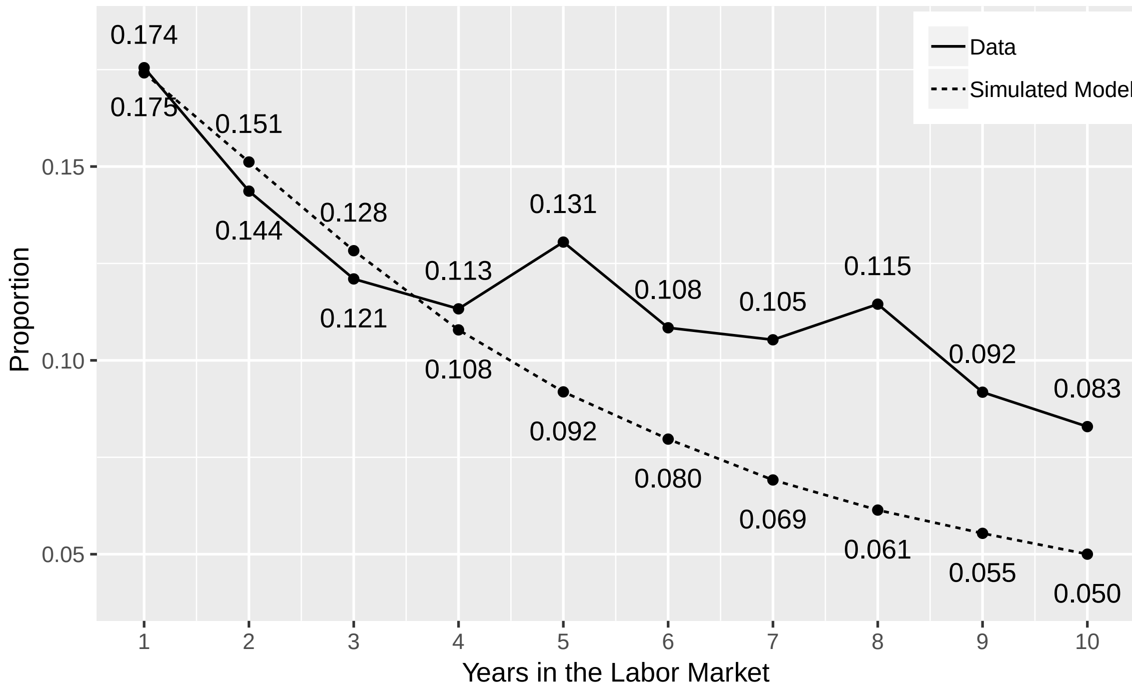
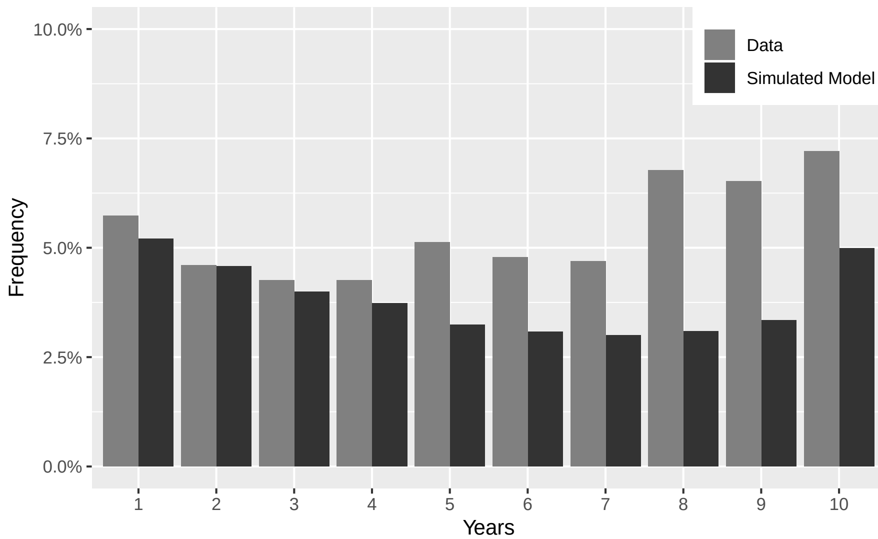
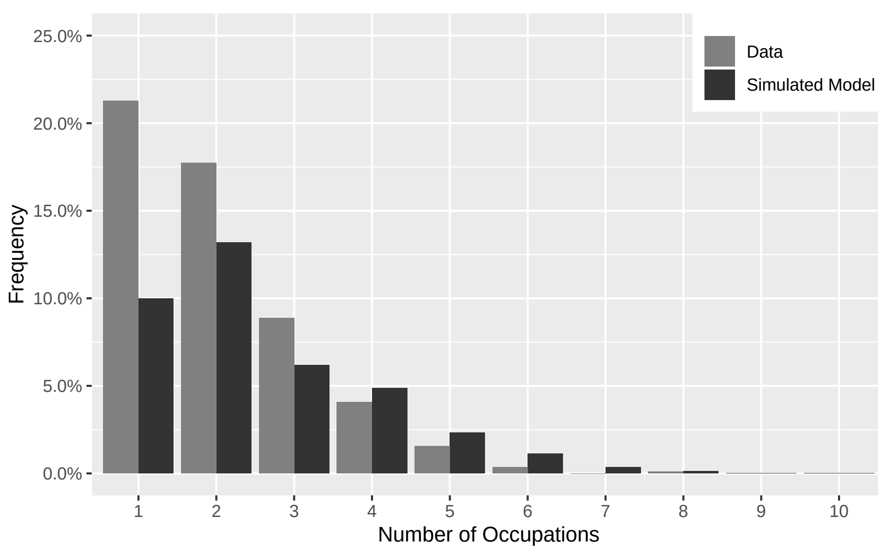


Figure 1.4: Proportion of Workers who Change Occupations in a Year



(a) Distribution of the Number of Years That a Worker Spend in the LM before the Best-matched Occupation



(b) Distribution of the Number of Occupations That a Worker Tries out before the Best-matched One

Figure 1.5: Paths to the Best-matched Occupations in the Data and the Simulated Model

Notes: The best-matched occupation is a worker's last occupation in the first ten years of her career. 46.05% of the workers in the data and 61.75% of the workers in the simulated model move to their best-matched occupations on their first tries. I omit such workers in the figure to have proper scales for the rest of the workers.

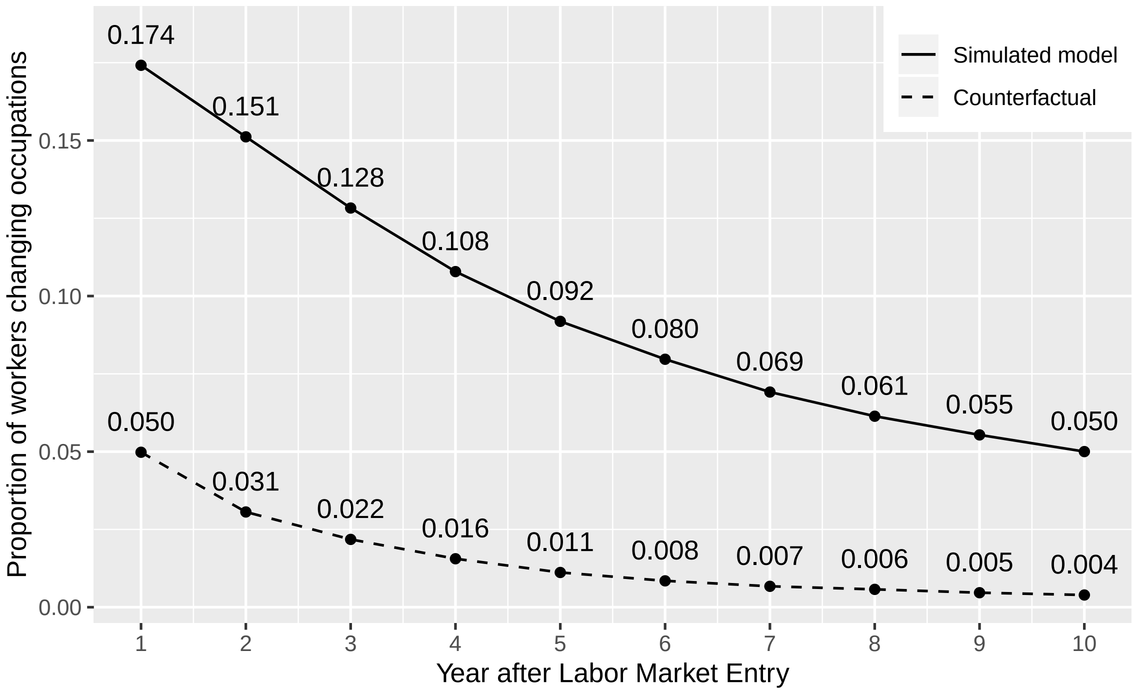
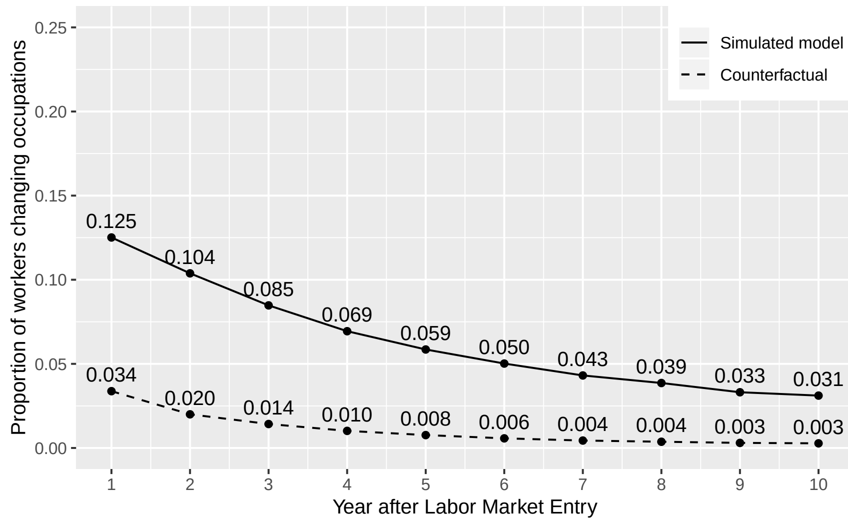
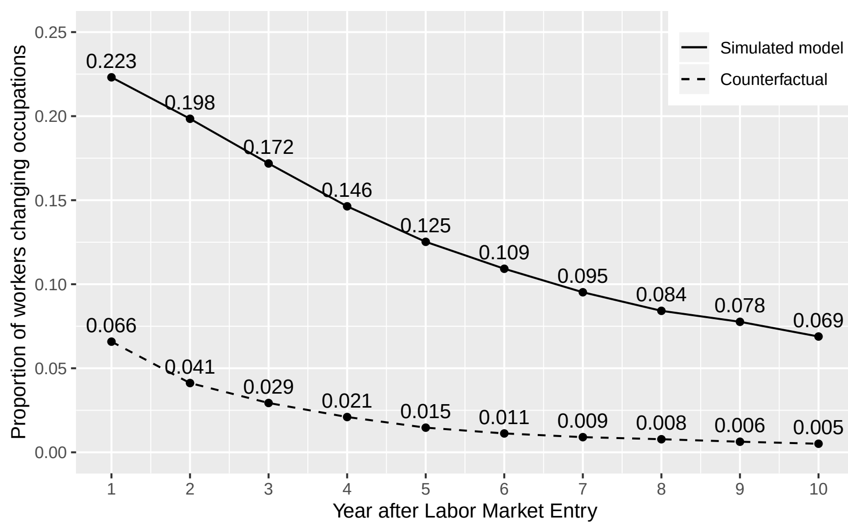


Figure 1.6: Occupational Mobility in the Experiment of a S.D. Increase in the Strength



(a) Workers with Strong Comparative Advantages



(b) Workers with Weak Comparative Advantages

Figure 1.7: Occupational Mobility of Workers with Different Strength of Their Comparative Advantages

Notes: A worker has a weak comparative advantage if her average distance between the productivities in the best-matched occupation and in the other two is smaller than the median distance. Otherwise, she has a strong comparative advantage. In the counterfactual experiment, I enlarge the strength of workers' comparative advantages by increasing their productivities in the best-matched occupations by one standard deviation of the strength. The strength of a worker's comparative advantage is measured by the average distance between the productivities in the best-matched occupations and the other two occupations. Enlarging the strength does not change a worker's rank of the strength of her comparative advantage in the population.

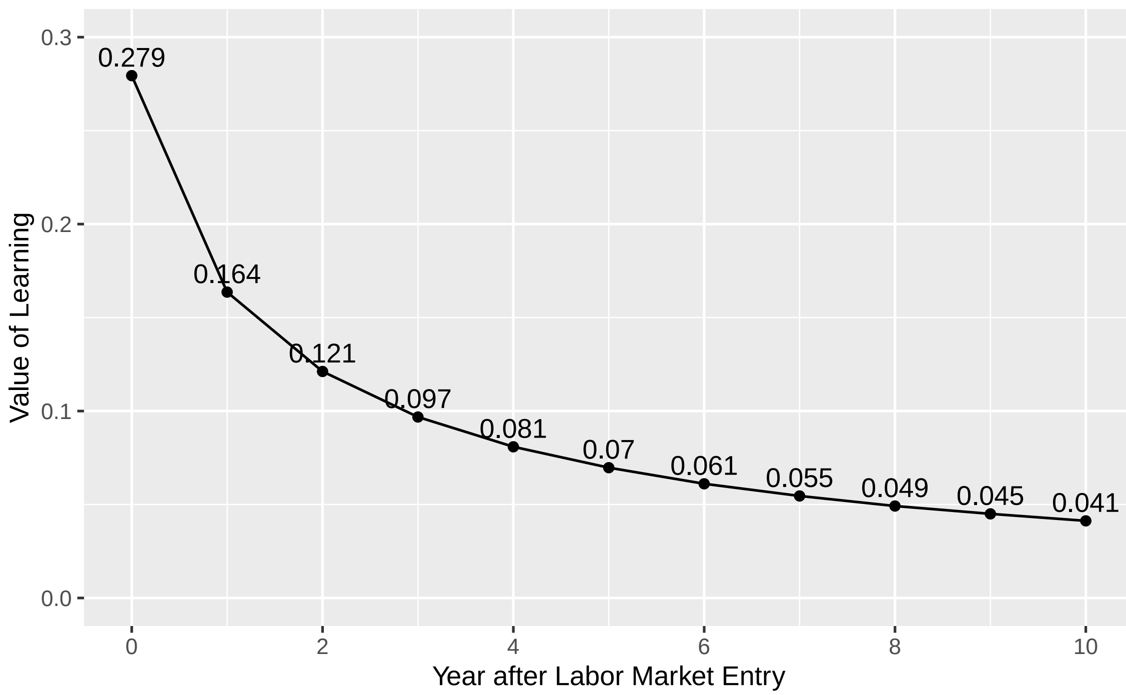


Figure 1.8: The Mean of the Value of Learning by Labor Market Experience

Notes: The mean of value of learning is measured by the percentage of the mean of expected wages.

Chapter 2

Good Personality Traits in Bad Times: Does Conscientiousness Mitigate the Adverse Effects of Graduating in a Recession?

2.1 Introduction

The literature has well documented that college students who graduate in recessions experience persistent earning losses as they face lower-quality jobs at labor market entry. These workers gradually recover from initial shocks either by moving to better firms or because of internal adjustments within firms. These adverse effects, however, are unequal for college graduates, with those with higher earning potential experience smaller and less persistent earning losses.

Conscientiousness, one of the Big Five personality traits, is an important predictor of earnings. Workers with high levels of Conscientiousness tend to be organized, responsible, and hardworking[1]. Psychologists have long used Conscientiousness to predict job performance and earnings. Recently, a growing body of economic literature has begun to investigate the effects of personality traits, including Conscientiousness, on social-economic outcomes, finding that higher levels of this trait are associated with higher wages, better education outcomes, and healthier lifestyles as well as increased savings and life satisfaction.

This paper explores whether high levels of Conscientiousness help college graduates mitigate income losses resulting from graduating during a recession. Figure 2.1 reports the residual log annual income after accounting for labor market conditions at graduation, experience, year fixed effects, and race. The left panel suggests that workers with high levels of Conscientiousness earn more than those with low levels when they graduate in times of high unemployment. In contrast, as the right panel shows, workers with different levels of Conscientiousness have similar annual incomes when they graduate in times of low unemployment. This difference suggests that Conscientiousness may help workers to mitigate the adverse effects of graduating during a recession on earnings.

Using the college graduates from the National Longitudinal Survey of Youth 1979 (the NLSY79), this study finds that high Conscientiousness helps workers graduating in a recession mitigate their income losses. For example, a college graduate with a Conscientiousness level of 75% in this sample can mitigate most of the adverse impacts of graduating in years of a two percentage point higher unemployment rate than the mean. In contrast, a worker whose Conscientiousness is at the 25% level experience approximately an 8.5% loss of income per year over the first ten years of working experience. The mitigation effects of the former result from the adjustment

[1]The definition of Conscientiousness used here is from *APA Dictionary of Psychology* retrieved from `https://dictionary.apa.org/conscientiousness` at 12:24, March 01, 2020.

of different margins of labor supply. Workers high in Conscientiousness tend to work more weeks, are more likely to be have full-time jobs, and to work more hours in these full-time jobs as a response to adverse labor market entry conditions.

This study also explores the mitigation effects of high cognitive ability measured by the Armed Forces Qualifications Test (AFQT) as a comparison with Conscientiousness. Although cognitive ability is a standard predictor for earnings, in contrast to the strong mitigation effects of Conscientiousness, high cognitive ability does not help workers to moderate the adverse effects of graduating in recessions.

To my knowledge, this study is the first one investigating how Conscientiousness helps workers mitigate the persistent adverse effects on earnings if they graduate during a recession. Moreover, the findings here enrich our understanding of the mechanisms behind the strong association between Conscientiousness and earnings in a specific setting, that of graduating in a recession. It also emphasizes the importance of early childhood intervention programs as Conscientiousness is mostly developed in early childhood, meaning nurturing this trait at that time helps children address adverse conditions in adulthood.

2.2 Literature Review

2.2.1 Persistent Effects of Graduating in a Recession

Graduating in a recession has long-lasting effects on workers' labor market outcomes. Analyzing college graduates from U.S., Canada and Norway, Altonji, Kahn and Speer (2015); Oreopoulos, von Wachter and Heisz (2012); and Liu, Salvanes and Sørensen (2016) find that college graduates experience a persistent decline in earnings if they graduate during a recession. A one percentage point increase in the unemployment rate at graduation reduces log earnings by two to six percentage points in the first year for up to ten years. These earning losses are a combination of losses in both wages and working opportunities. Graduating during a recession reduces not only hourly wages but also the annual weeks worked and the probability of being employed or having full-time jobs.

The lasting reduction in the quality of jobs is an important source of persistent income loss. Oreopoulos, von Wachter and Heisz (2012) argue that this reduction accounts for at least 40% of income losses. The mismatch between majors and occupations or industries is another source for earning loss as students who graduate during a recession are less likely to find jobs in their best-matched occupations or industries (Altonji, Kahn and Speer, 2015; Liu, Salvanes and Sørensen, 2016). Both the mobility to better firms and adjustment within firms are important mechanisms for students recovering from graduating during a recession (Oreopoulos, von Wachter and Heisz, 2012).

College graduates bear unequal losses resulted from graduating during a recession. Those with lower earning potential experience larger and more persistent incomes losses than their counterparts from the same cohort if they graduate during a recession. In their study using colleges and majors to predict graduates' potential earnings, Oreopoulos, von Wachter and Heisz (2012) find that workers with lower predicted earnings are more affected by initial labor market conditions. Altonji, Kahn and Speer (2015) take a similar approach and group majors into different categories by their returns. They find that workers from high-return majors are less affected by high unemployment rates at graduation. One possible explanation for these heterogeneous effects is that workers with different earning potential receive job offers at different frequencies and with different qualities.

Research also finds long-lasting effects of labor market entry conditions on labor market outcomes for other educational groups. For example, Hershbein (2012) finds that high school graduates also experience wage losses if they graduate during a recession, albeit the effect is smaller than college graduates. In addition, Oyer (2008) finds that stock market at graduation, his measure of labor market entry conditions for MBAs, have a lasting effect on their careers as well.

2.2.2 Personality Traits

Personality traits are important predictors for social-economic outcomes, and the "Big Five" is the common taxonomy used in personality psychology. (See John and Srivastava (1999) for a review of the history and measurement of the "Big Five".) According to the American Psychiatric Association, the Big Five personality traits include

- Openness to Experience: The tendency to be open to new aesthetic, cultural, or intellectual experience;
- Conscientiousness (vs. Lack of direction): The tendency to be organized, responsible, and hardworking;
- Extraversion: An orientation of one's interests and energies toward the outer world of people and things rather than the inner world of subjective experience;
- Agreeableness: the tendency to act in a cooperative, unselfish manner;
- Neuroticism (vs. Emotional Stability): A chronic level of emotional instability and proneness to psychological distress.[2]

[2]The initials of the Big Five, O · C · E · A · N, form an easily remembered acronym. The definitions provided here come from the online version of *APA Dictionary of Psychology*, retrived from `https://dictionary.apa.org/` at 23:35, March 06, 2020.

Of these five traits, Conscientiousness is the one most closely related to labor market outcomes.

Psychologists have long studied the effects of personality traits on various social-economic outcomes. Based on the meta-analysis of previous papers, Barrick and Mount (1991) conclude that of the five personality traits, only Conscientiousness has a consistent and positive relationship with various measures of job performance across occupations. In further research, Barrick, Mount and Strauss (1993) find similar results using data from sales representatives. They argue that workers high in Conscientiousness have better job performance because they are more motivated than others. Judge et al. (1999) extend the outcomes to job satisfaction, income, and occupational status, finding that Conscientiousness also positively predicts these outcomes.

Economists began conducting research about personality traits relatively late compared to psychologists. However, in recent years, we have seen a growing literature focused on the effects of personality traits on various labor market outcomes. For example, Borghans et al. (2008) and Almlund et al. (2011) thoroughly discuss the interface between personality psychology and economics in their papers, both finding that higher levels of Conscientiousness are associated with higher wages, better education outcomes, a more healthy lifestyle as well as increased savings and life satisfaction. In more recent research, Gensowski (2018) finds a direct effect of Conscientiousness and an indirect effect of Conscientiousness through education on lifetime earnings for men with high IQ. Consistent with this indirect effect, Lundberg (2013) finds that Conscientiousness increases the probability of college completion except for male graduates from disadvantaged families. Uysal and Pohlmeier (2011) focus on the effects of personality traits on worker employment status, their results indicating that a high level of Conscientiousness increases the instantaneous probability of finding a job and decreases subsequent employment durations. They argue that high Conscientiousness not only motivates workers to search for jobs but also increases the probability of receiving offers by signaling a desirable attribute to potential employers. Instead of studying the effects of five personality traits on one specific labor market outcome, Prevoo and ter Weel (2015) investigate the specific effects of Conscientiousness on various labor market outcomes, finding that high levels of Conscientiousness increase hourly wages, educational outcomes as well as the probability of being employed, working in skill-intensive jobs and having monthly savings. Moreover, by investigating the lower-order structure of Conscientiousness, they suggest that the effects of this trait are mainly driven by its three facets of reliability, decisiveness, and impulse control.

2.3 Data

2.3.1 Sample Construction

This study uses data from the National Longitudinal Survey of Youth 1979 (NLSY79), a nationally representative longitudinal survey started by the Bureau of Labor Statistics in 1979. 12,686 youths between the ages of 14 and 22 were interviewed initially and followed annually until 1994 and biennially thereafter. Most of the college graduates in the NLSY79 graduated from college in the 1980s, a period involving multiple peaks and troughs in the economy. Furthermore, the NLSY79 includes rich information on respondents' personality traits, cognitive ability, educational outcomes, and employment history, all essential for this research.

This study focuses on college graduates. Of the 11,406 individuals who never worked in the military, 2,014 are college graduates with valid graduation dates. Following the selection criteria of the reasonable graduation date in Kahn (2010) and Altonji, Kahn and Speer (2015), I restrict the sample to the 1,658 workers who graduate between 1979–1989. Next, I restrict the sample to male college graduates, and finally, to workers who have valid cognitive ability and personality traits as well as at least one valid observation of the annual income in the first ten years after graduation.[3] Based on these criteria, 497 male college graduates comprise the final sample. Table 2.1 reports the process of sample construction.

As the national economy is most relevant for college graduates, I use the annual average of the national monthly unemployment rates (hereafter referred to as the national unemployment rates) as the indicator of labor market conditions at graduation.[4] Table 2.2 reports the size of the graduation cohorts and the national unemployment rates in the year of graduation. The national unemployment rate captures the recessions in the early 1980s and the subsequent recovery, indicating substantial variations among different graduation cohorts. The unemployment rate at graduation ranges from 5.3% to 9.7%, with a median of 7.2%. The unemployment rates from 1981 to 1984, which are higher than the median unemployment rate at graduation, are classified as high unemployment rates; 44.18% of workers graduated in the years with high unemployment rates, while the remaining graduated in years with low unemployment rates.

This study focuses on the labor market outcomes in the first ten years after graduation because previous literature finds that adverse effects disappear after this

[3]The mitigation effects of Conscientiousness may be different between the genders. First, male and female college graduates experience different losses resulted from graduating during a recession (Kondo, 2015). Second, studies have found mixed results about the gender difference in the effects of Conscientiousness. Mueller and Plug (2006) find that Conscientiousness is more important for female workers than male workers, while Prevoo and ter Weel (2015) do not find a significant difference between the genders.

[4]The annual average of the national monthly unemployment rates was downloaded from the website of the Bureau of Labor Statistics at `https://data.bls.gov/PDQWeb/la` at 09:27, February 19, 2020.

time period(Oreopoulos, von Wachter and Heisz, 2012; Altonji, Kahn and Speer, 2015; Liu, Salvanes and Sørensen, 2016). Labor market outcomes in the year of graduation are excluded from the analysis because not all workers graduated before the interview but spent a large proportion of their time on the labor market in that year. Table 2.3 reports the number of workers interviewed in my sample over the first ten years after graduation. In the first five years after graduation, approximately 490 workers were interviewed per year. After that, the number of workers decreases as some begun to be interviewed biennially. This change in the interview frequency explains the main decrease in the number of workers interviewed per year.

2.3.2 Personality Traits and Cognitive Ability

Personality traits in the NLSY79 are measured by the ten-item personality inventory of the Big Five personality traits (TIPI) in the 2014 survey. TIPI, developed by Gosling, Rentfrow and Swann Jr. (2003), asks respondents to rate themselves in relation to the Big Five using a 7-point scale from "disagree strongly" to "agree strongly". The score of a personality trait is determined by averaging the rates of the corresponding pair of opposing descriptions, ranging from 1 to 7 with a step of 0.5.[5] For example, the positive description of Conscientiousness is "Dependable, self-disciplined", and the negative description is "Disorganized, careless". Workers who report they are dependable and self-disciplined, but not disorganized nor careless have high scores of Conscientiousness. In this study, the personality traits are standardized among all workers who have valid personality traits in the NSLY79 with the corresponding custom weights.[6] Table 2.4 summarizes the questions used in the NLSY79

[5]Before taken the average, the score of the negative description is reserved by the following formula: $8 -$ the respondent's rate.

[6]The NLSY79 provides the custom weights through its website. `https://www.nlsinfo.org/weights/nlsy79`.

to measure the Big Five personality traits. This study focuses on the mitigation effects of Conscientiousness and uses the other four personality traits as controls.

As personality traits are measured in the 2014 survey when workers have already worked approximately 30 years in the labor market, there are concerns that labor market outcomes in the first ten years and personality traits measured in the 2014 survey are both affected by labor market entry conditions. However, some Economic studies, using longitudinal data, find that personality traits are stable over adulthood. For example, Cobb-Clark and Schurer (2012) find that personality traits are stable in adulthood over a four-year window. Further, Anger, Camehl and Peter (2017) find that factory close only increases Openness to Experience for the average displaced worker, but does not change other personality traits over an eight-year window.

To assess the inter-dependency problem, this study compares the personality traits of workers who graduated in times of high unemployment with those who graduated in times of low unemployment in Table 2.5. The statistics are weighted by the custom weights of workers who report their personality traits. The first two columns of Table 2.5 suggest that college graduates, on average, exhibit higher scores for personality traits than non-college graduates except for Agreeableness. More importantly, the last column of Table 2.5 shows that there is no significant difference in Conscientiousness, Openness, Extraversion, and Agreeableness among different graduation cohorts, suggesting that there is no direct evidence indicating that Conscientiousness is affected by labor market entry conditions. The unweighted results can be found in Table 17 in the Appendix. As a robustness check, I follow Heineck and Anger (2010) and use age-adjusted personality scores to repeat the analysis in the main paper. The results using age-adjusted personality scores, which are reported in Appendix D, are similar to the results reported in the paper.

Following the literature, this study uses the Armed Forces Qualifications Test (AFQT) score in the 1981 survey to measure cognitive ability. The scores are re-normed by the NLS staff to account for age effects.[7] The AFQT scores are standardized among all workers who have valid AFQT scores in the NLSY79 with the corresponding custom weights. Table 2.5 reports the AFQT scores for workers who graduated in times of both high and low unemployment. The statistics are weighted using the custom weights of workers with valid personality traits. The unweighted statistics can be found in Table 17. Overall, college graduates have higher AFQT scores than other workers. Moreover, the difference in AFQT scores between the two graduation cohorts is not significant, suggesting that labor market entry conditions do not affect the AFQT scores.

2.3.3 Outcome Variables

Log annual income, the primary labor market outcome in this study, reflects the effects of bad labor market entry conditions on both the hourly wage and the working status. The NLSY79 asks respondents directly for their annual income in the previous year. This study restricts the income sample to workers who reported annual incomes of more than 100 dollars based on 1979 values and who were not enrolled in school on May 01 of that year. The enrollment status in the previous year is available in the NLSY79 for years before 1994 as the NLSY79 was conducted annually in this time period. However, there is no such information after 1994 because the NLSY79 has been conducted biennially since then. Thus, this study, following the method used by Altonji, Kahn and Speer (2015), use the enrollment status in the current year as the basis for the restrictions for previous annual incomes for years

[7] AFQT-3 is the re-normed score. Check the NLSY79 website for details. `https://www.nlsinfo.org/content/cohorts/nlsy79/topical-guide/education/aptitude-achievement-intelligence-scores`

after 1994. For example, I use employment status on May 01, 1996, to restrict annual income observations for 1995.

The hourly wage, another important labor market outcome in this study, measures the wage in the current or most recent job as of the interview date. This study restricts observations to workers who have valid annual incomes. As the annual income was reported in the following year and respondents have been interviewed biennially since 1994, this study uses the annual income in the previous year to restrict the wage observations in the current year for years after 1994. In addition, wage observations of less than one dollar based on 1979 values are dropped.

The remaining labor market outcomes measure different dimensions of working status. First, annual weeks worked measures the number of weeks worked in the last year. For this outcome, the sample is restricted to those who report annual incomes. Second, the employment status, which measures the status in the week before the survey week, is collapsed into two categories: 1 for employed and 0 for the other status. The other two outcomes, full-time employment and hours worked per week in these full-time jobs, are both constructed using the usual hours worked per week in the current or most recent jobs. Figure 2.2 reports the weighted distribution of weekly working hours in the first ten years after graduation for workers who were employed in the week before the interview week. The unweighted distribution can be found in Figure 9. Conditional on being employed, workers who graduated in times of high unemployment are less likely to work exactly 40 hours and are more likely to work overtime than those who graduate in times of low unemployment. Based on this variable and the employment status, I define full-time employment as working for at least 35 hours per week and being employed in the week before the interview week.

Table 2.6 reports the labor market outcomes in the first ten years after graduation for workers who graduate in times of both high and low unemployment. These statistics are weighted using the custom weights of workers who report personality traits, while the unweighted results can be found in Table **??** in the Appendix. Table 2.6 suggests that college graduates are at a high level of employment, regardless of labor market entry conditions. On average, they work 49–50 weeks per year. In addition, more than 90% of them are employed, with more than 85% full-time jobs. Furthermore, they, on average, work more than 45 hours per week at their full-time jobs. Table 2.6 also shows that on average workers who graduate in times of high unemployment have significantly lower wages and work significantly more at their full-time jobs than those graduating in good years. The comparison of the labor market outcomes also reveals significant differences in the employment status among the graduation cohorts. However, these differences should be taken with great caution as they become much smaller to the point of being insignificant in the unweighted table.

Table 2.7 compares the weighted labor market outcomes at different stages of careers, with Table 19 in the Appendix comparing the unweighted outcomes. The top, middle, and bottom panels in Table 2.7 report the comparison of labor market outcomes in 1–3 years, in 4–6 years and in 7–10 years after graduation. On average, workers graduating in years of high unemployment earn lower incomes and hourly wages during the first three years, but the losses shrink in later years.

2.4 The Mitigation Effects

2.4.1 Empirical Strategy

This study follows the empirical strategy in Altonji, Kahn and Speer (2015) to explore the effects of Conscientiousness on mitigating the adverse effects of graduating in a recession using the following specification:

$$\begin{aligned} Y_{ict} = & U_c\beta_1 + +(U_c \times PE_{it})\beta_2 \\ & + \mathbf{A}_i\boldsymbol{\beta_3} + (\mathbf{A}_i \times PE_{it})\boldsymbol{\beta_4} + (U_c \times \mathbf{A}_i)\boldsymbol{\beta_5} + (U_c \times \mathbf{A}_i \times PE_{it})\boldsymbol{\beta_6} \\ & + \mathbf{X_{it}}\boldsymbol{\beta_7} + \epsilon_{ict}, \end{aligned} \tag{2.1}$$

where Y_{ict} represents labor market outcomes in year t for individual i from graduation cohort c, including the log annual income, log hourly wage, annual weeks worked, probability of being employed, probability of having full-time jobs, and hours worked per week at full-time jobs, and U_c is the national unemployment rate of cohort c's graduation year, from which the mean unemployment rate at graduation (7.46) is subtracted. A_i are five personality traits and AFQT scores, which are demeaned as well. Subtracting means from these variables helps us interpret the main effects of unemployment rates at graduation and the main effects of personality traits and AFQT on various labor market outcomes in specifications with many interactions, specifically β_1 and $\boldsymbol{\beta}_3$, which are effects of unemployment rates at graduation and the effects of traits when $PE_{it} = 0$. PE_{it} is individual i's potential experience in year t, defined as the years after graduation. This study excludes labor market outcomes in the year of graduation in the regressions because workers did not fully commit their time to the labor market in that year. Further, this study subtracts one from PE_{it} so that the PE_{it} starts at 0. X_{it} are control variables, including a quadratic form of potential experience, the cubic time trend, contemporaneous unemployment rates, and race. The standard errors are clustered by the graduation cohort, the level of variation underlying U_c.

2.4.2 Marginal Effects

To better understand the mitigation effects, I compare the marginal effects of the unemployment rates at graduation for workers with different levels of Conscientiousness or AFQT. Equation 2.2, derived from Equation 2.1, represents the marginal effects of unemployment rate at graduation on labor market outcomes for a worker whose Conscientiousness is given and whose other personality traits and AFQT score are at the mean levels.

$$ME_{ict}^{Cons} = \beta_1 + PE_{it} \times \beta_2 + A_i^{Cons} \times \beta_5^{Cons} + A_i^{Cons} \times PE_{it} \times \beta_6^{Cons}, \tag{2.2}$$

where β_1 is the effect of labor market entry conditions in the first year after graduation, a value expected to be negative, and β_2 describes how the effects of entry conditions evolve over time. If β_1 and β_2 have opposite signs, then the effect of labor market entry conditions decreases over time.

Equation 2.3 defines the mitigation effect of Conscientiousness, which is the change in the marginal effects, ME_{ict}^{Cons}, due to the change in Conscientiousness. It depends on two parts: β_5^{Cons} is the mitigation effect in the first year, which is expected to have a sign opposite of β_1 for most of the labor market outcomes; β_6^{Cons} describes how the mitigation effect evolves over time. If β_5^{Cons} and β_6^{Cons} have opposite signs, then the mitigation effect decreases over time.

$$\Delta ME_t^{Cons} = \Delta A^{Cons} \times \beta_5^{Cons} + \Delta A^{Cons} \times PE_{it} \times \beta_6^{Cons}. \tag{2.3}$$

Similarly, the marginal effects of labor market entry conditions for a worker whose AFQT score is given and whose personality traits are at the mean level is

$$ME_{ict}^{AFQT} = \beta_1 + PE_{it} \times \beta_2 + A_i^{AFQT} \times \beta_5^{AFQT} + A^{AFQT}{}_i \times PE_{it} \times \beta_6^{AFQT}. \quad (2.4)$$

Further, the mitigation effects of AFQT on the adverse effects of graduating in a recession is represented as

$$\Delta ME_t^{AFQT} = \Delta A^{AFQT} \times \beta_5^{AFQT} + \Delta A^{AFQT} \times PE_{it} \times \beta_6^{AFQT}. \quad (2.5)$$

2.4.3 Empirical Results

2.4.3.1 Annual Income

College graduates experience persistent income losses if they graduated in times of high unemployment. Table 2.8 reports the adverse effects on log annual incomes. In Column (1), following the specification in Kahn (2010), the regression controls for the AFQT. Then I gradually add personality traits, the interaction between the traits (AFQT and five personality traits) and unemployment rates at graduation, and the full interaction among the traits, potential experience and unemployment rates at graduation in Column (2), Column (3) and Column (4). Column (4) reports the result from the preferred specification defined in Equation 2.1.

The first row of Table 2.8 reports the effect of the national unemployment rate at graduation on the log annual income in the first year after graduation. This effect is consistent among different specifications for workers exhibiting mean traits. On average, college graduates who graduate in a recession (two percentage points increase from the mean of 7.46) experience nine percentage point loss in their log annual incomes compared with those who graduate in years with a mean unemployment rate.

The magnitude found here is between the founding in Liu, Salvanes and Sørensen (2016) and that in Altonji, Kahn and Speer (2015) and Oreopoulos, von Wachter and Heisz (2012).[8] The second row reports the evolution of the effect of the labor market entry condition over the first ten years after graduation. In most of the specifications, the effects decreases to less than 1% after ten years from graduation. The persistence of the effect on annual income is consistent with the results in Liu, Salvanes and Sørensen (2016), Altonji, Kahn and Speer (2015), and Oreopoulos, von Wachter and Heisz (2012).

Among all personality traits, Conscientiousness is the only one that exhibits a consistent effect on annual incomes across specifications. On average, one standard deviation increase in Conscientiousness increases the log annual income by 13 percentage points in the first year after graduation; it then decreases by 1.2 percentage points per year until it disappears after ten years. Most importantly, the coefficient of the interaction term between Conscientiousness and the unemployment rate at graduation is positive, suggesting that high levels of Conscientiousness mitigate the negative effects of graduating in bad years on annual incomes. Moreover, the full interaction term among Conscientiousness, unemployment rates at graduation, and potential experience is negative, suggesting that the mitigation effects decreases over time. This decreasing in the mitigation effect is consistent with the evolution of the effect of unemployment rates at graduation on annual incomes. As the negative main effect decreases over time, we expect the mitigation effect to decrease as well.

In addition to Conscientiousness, AFQT is the other trait that increases annual

[8]The difference may be due to the different samples and the different labor market shocks at graduation in the three studies. Liu, Salvanes and Sørensen (2016) use Norwegian college gradates who graduated between 1988–2003, Altonji, Kahn and Speer (2015) use American male and female college graduates who graduated between 1974 and 2011, and Oreopoulos, von Wachter and Heisz (2012) use Canadian male college graduates who graduated between 1976 and 1995. Kahn (2010) uses a similar sample to mine. However, she does not study the effects on annual incomes.

incomes, but it does not help workers to mitigate the negative effects of graduating in a recession. The coefficient of the interaction term between AFQT and unemployment rate at graduation is small and insignificant, as is the coefficient of the full interaction term.

To better understand the evolution of these effects, Panel A and Panel B in Figure 2.3 plot the marginal effects of the unemployment rate at graduation on the log annual income for workers whose Conscientiousness or AFQT is at the 25% and 75% level, with remaining traits being equal to the means. In addition, Panel C in Figure 2.3 plots the mitigation effects of Conscientiousness or AFQT on the adverse effects of graduating in a recession on annual incomes by comparing the marginal effects in Panel B and Panel A. Panel C visualizes Equation 2.3 and Equation 2.5. Panel A shows that workers who have low Conscientiousness scores and those who have low AFQT scores are impacted by high unemployment rates at graduation. However, both types of workers later recover from the initial adverse conditions. Panel B tells a different story. Workers with high scores in Conscientiousness are sheltered from the income losses resulted from the adverse labor market entry condition, while workers with high AFQT scores experience persistent losses in their annual incomes. Panel C suggests that high Conscientiousness significantly mitigates the effects of the adverse labor market entry condition on annual incomes while high AFQT does not. In summary, an increase in Conscientiousness from the 25% level to the 75% level almost completely mitigates the adverse effect of graduating in bad years on labor market outcomes, while the same increase in AFQT does not help workers overcome the adverse effects.

2.4.3.2 Hourly Wage

This part focuses on the hourly wage, first comparing the adverse effect of graduating in a recession on log hourly wages with the literature, followed by an analysis of whether high Conscientiousness or high AFQT scores help workers to mitigate this adverse effect.

Similar to Table 2.8, Table 2.9 reports the results of four specifications. Graduating in a recession (two percentage points increase in the unemployment rate from the mean) reduces the log hourly wage by 12.8% in the first year, which then decreases by 1% per year thereafter. Ten years after graduation, the adverse effects on log hourly wage reduces to 2.8%. The main effect is consistent with the result in Kahn (2010), who also analyzes the college graduates in the NLSY79.[9] However, the adverse effect in this study lasts for a shorter period than the result in Kahn (2010) but is consistent with Altonji, Kahn and Speer (2015).

Although both high scores in Conscientiousness and in AFQT significantly increase the hourly wage, nether has a significant mitigation effect on cushioning the adverse effects of graduating in a recession. Figure 2.4 visualizes the marginal effects for workers whose Conscientiousness or AFQT scores are at the 25% level or 75% level as well as the mitigation effects of both traits. Panel A and Panel B suggest that regardless of these scores, college graduates who graduate in a recession invariably experience wage losses. These losses decrease over time. Although none of the mitigation effects in Panel C is significant, it is worth noting that their directions are different. The mitigation effect of AFQT has a downward trend and becomes negative in later years, while the mitigation effect of Conscientiousness is roughly constant and always positive.

[9]Kahn (2010) focuses on the white men subsample while I also include black and Hispanic male college graduates.

2.4.3.3 Working Time and Employment Status

This section analyzes the remaining labor market outcomes related to working time and employment status, beginning with the mitigation effects on annual weeks worked. The regression results about annual weeks worked can be seen in Table 2.10. The main effect of unemployment rates at graduation is negative but not significant, reaching zero within four years after graduation. The main effect found here is smaller and less persistent than the results found by Kahn (2010).

Despite the insignificant main effect of labor market entry conditions, Conscientiousness has not only a strong main effect and but also a significant mitigation effect on annual weeks worked. A one standard deviation increase in Conscientiousness increases the number of weeks worked in a year by 0.796, an effect that lasts up to ten years. In addition, compared with workers who graduated in years with the mean unemployment rate, a one standard deviation increase in Conscientiousness additionally increases the annual weeks worked by 0.42 for workers who graduate in years when unemployment rates are one percentage point higher than the mean. This mitigation on effect disappears after eight years. In contrast AFQT has no effects on annual weeks worked.

Figure 2.5 repeats the analysis in Figure 2.3 for annual weeks worked. Panel C suggests that workers who have high Conscientiousness scores may alleviate the adverse effects of graduating in a recession on annual earnings by increasing weeks worked.

Next, the effects on the employment status in the week before the interview week are displayed in Table 2.11. The unemployment rate at graduation has almost no effect on the probability of being employed. As more than 90% of college graduates have jobs in my sample period, there is little room for college graduates to adjust their labor supply behaviors for this dimension. My result is consistent with the insignificant results found by both Kahn (2010) and Altonji, Kahn and Speer (2015). Regarding the mitigation effects, due to the relatively high employment rate and the little room for adjustment, neither high Conscientiousness nor AFQT scores significantly increase the probability of being employed. The marginal effects and mitigation effects over time are plotted in Figure 2.6.

Although the probability of being employed may not be sensitive to labor market entry conditions, the unemployment rate at graduation might affect the probability of having full-time jobs and hours worked per week in these full-time jobs. Accordingly, workers with different traits may make different adjustments in these dimensions.

The investigation here begins by looking at the probability of having full-time jobs, with results being reported in Table 2.12. On average, workers who graduate in a recession (a two percentage point increase from the mean level) are 4.4 percentage points less likely to have full-time jobs in the first year after graduation, subsequently decreasing by one percentage point per year. Conscientiousness has a large main effect on the probability of having full-time jobs. On average, workers high in Conscientiousness are more likely to have full-time jobs regardless of their labor market entry conditions. In addition, high Conscientiousness helps workers mitigate the adverse effects on the probability of having full-time jobs as the coefficient of the interaction term between Conscientiousness and the unemployment rate at graduation is significant and positive. This effect has a similar magnitude to the main effect of the unemployment rate at graduation on the probability of having full-time jobs. In contrast, high AFQT scores, on average, do not increases the probability of having full-time jobs. In fact, high AFQT scores augment the adverse effects of graduating in a recession.

Figure 2.7 reports the evolution of the marginal effects for workers with different traits and the mitigation effects of Conscientiousness and AFQT. Both the marginal effects and the mitigation effects disappear within five years after graduation.

Finally, this section explores the effects on the hours worked per week in full-time jobs, the regression results being reported in Table 2.13. Graduating in a recession increases slightly less than one hour of working time for full-time workers in the first year, an effect that diminishes over time. This positive effect on working hours suggests that workers attempt to work more to compensate for the lower hourly wage and the lower probability of having full-time jobs when they graduate during recessions.

On average, high Conscientiousness does not increase working hours in full-time jobs as workers already work approximately 45 hours. However, if workers graduate in a recession, those high in Conscientiousness try to increase their working hours in their full-time jobs, a context-specific effect that increases over time. In contrast, workers with high AFQT scores do not work more hours in full-time jobs regardless of the labor market entry conditions. Figure 2.8 reports the marginal effects and mitigation effects on weekly working hours in full-time jobs. Different from other outcomes, the marginal effects are positive initially and decrease over time, except for workers with Conscientiousness at the 75% level. Graduating in a recession permanently increases working hours in full-time jobs for workers with high Conscientiousness scores. In addition, as Panel C suggests, high Conscientiousness augments the positive effects of graduating in a recession on working hours, an effect that grows over time and, thus, is different from the mitigation effects for other labor market outcomes.

2.5 Conclusion

Empirical results show that high Conscientiousness helps college graduates who graduate in a recession to fight against income losses. In addition, results involving various labor market outcomes indicate that the mitigation effects on income losses primarily result from workers' adjustments in their labor supply. If workers who have high Conscientiousness graduate during a recession, they tend to work more weeks, try harder to find full-time jobs, and work more hours in these full-time jobs to compensate for income losses. In contrast, this study does not find that high AFQT scores mitigates the adverse effects of graduating in a recession.

Tables

Table 2.1: Sample Construction

Criteria	Number of Individuals
Workers in the NLSY79	12686
Non-military sample	11406
Have college graduation date	2124
Graduate btw 1979–89	1658
Male workers	795
Valid cognitive ability	771
Valid personality	507
Valid annual incomes in the first ten years after graduation	498

Table 2.2: Sample Size of College Graduates Cohorts

Year of Graduation	U at Graduation	U group	Number of Workers
1979	5.8	Low	17
1980	7.1	Low	26
1981	7.6	High	38
1982	9.7	High	54
1983	9.6	High	52
1984	7.5	High	76
1985	7.2	Low	80
1986	7.0	Low	66
1987	6.2	Low	42
1988	5.5	Low	22
1989	5.3	Low	25
Total Number of Workers			498
Mean Unemployment Rate at Graduation			7.46
Median Unemployment Rate at Graduation			7.2

Note
[1] The unemployment rate at graduation is high if it is higher than median unemployment rate at graduation in the sample. Otherwise, the unemployment is low.

Table 2.3: Sample Size in Years after Graduation

	Graduation Year						
Years after Graduation	1979–84	1985	1986	1987	1988	1989	Total
1	260	79	64	42	22	25	492
2	262	80	65	42	22	25	496
3	258	80	66	41	22	25	492
4	258	80	64	41	22	25	490
5	258	79	65	41	22	24	489
6	257	80	64	41	22	—	464
7	256	79	64	42	—	24	465
8	254	79	66	—	22	—	421
9	256	80	—	41	—	23	400
10	255	—	64	—	22	—	341

Note:
[1] These are workers who are interviewed each year in my sample.

Table 2.4: TIPI Questionnaire

Big Five Traits	Positive Description	Negative Description
Openness	Open to new experiences, complex	Conventional, uncreative
Conscientiousness	Dependable, self-disciplined	Disorganized, careless
Extraversion	Extraverted, enthusiastic	Reserved, quiet
Agreeableness	Sympathetic, warm	Critical, quarrelsome
Emotional Stability	Calm, emotionally stable	Anxious, easily upset

Notes:

[1] In the survey, workers were asked "Here are some personality traits that may or may not apply to you. You will hear several pairs of personality traits that are related but not exactly the same. Using a scale of 1 to 7, where 1 means 'disagree strongly' and 7 means 'agree strongly' rate how well each pair of traits applies to you, even if one characteristic applies more strongly than the other."

[2] I group the descriptions by their corresponding traits and whether it is reverse-scored. The presentation of ten questions here are different from the presentation in the survey.

[3] The score of a trait is the average score of a corresponding pair of a positive description and a negative description. The score of a negative description is reversed as $8 -$ raw score. Final scores range from 1 to 7 with a step 0.5. Personality traits in the paper are standardized among workers who have valid personality traits using the corresponding custom weights.

[4] Source: the attitudes and personality section in the NSLY79 2014 questionnaire. Visited on 10:41, March 07, 2020. `https://www.nlsinfo.org/sites/nlsinfo.org/files/attachments/141219/nlsy79r26mainquex103114_ATT.html`

Table 2.5: Mean Personality Traits and AFQT of Different Graduation Cohorts

	High U at grad.	Low U at grad.	Difference
Openness	0.136	0.137	-0.001
	(0.8)	(0.954)	[0.08]
Conscientiousness	0.058	0.073	-0.015
	(0.8)	(0.936)	[0.079]
Extraversion	0.146	0.05	0.096
	(0.828)	(0.996)	[0.083]
Agreeableness	-0.14	-0.103	-0.037
	(0.867)	(0.867)	[0.078]
Emotional stability	0.099	0.23	-0.131*
	(0.852)	(0.859)	[0.077]
AFQT	0.97	0.88	0.09
	(0.676)	(0.682)	[0.061]

Notes:

[1] The unemployment at graduation is high if it is higher than the median unemployment rate at the graduation (7.2). Otherwise, the unemployment rate is low.

[2] Workers are weighted by the custom weights of respondents who have valid personality traits. Unweighted corresponding statistics are in Table 17.

[3] The standard deviations are in the parentheses. The standard errors are in the brackets.

Table 2.6: Labor Market Outcomes of Different Gradation Cohorts

Labor market outcomes	High U at graduation	Low U at graduation	Difference
Mean Log annual income	9.642	9.663	-0.021
	(0.633)	(0.606)	[0.02]
Mean Log hourly wage	1.886	1.942	-0.056***
	(0.502)	(0.492)	[0.017]
Weeks worked in a year	49.623	49.307	0.316
	(6.968)	(7.903)	[0.244]
Proportion of employed	0.933	0.911	0.022***
	—	—	[0.008]
Proportion of full-time jobs	0.879	0.857	0.022**
	—	—	[0.01]
Mean hours worked per week	46.144	45.656	0.488*
(Conditional on full-time jobs)	(8.642)	(9.351)	[0.287]

Notes:
[1] Standard deviations are in the parentheses, and standard errors for mean comparisons are in the brackets.
[2] ***, ** and *: Significant at the 1, 5 and 10 percent level
[3] Statistics are weighted by the custom weights of workers who were interviewed for personality traits. See Table **??** for unweighted comparisons.

Table 2.7: Labor Market Outcomes of Different Gradation Cohorts across Years

Labor market outcomes	High U at graduation	Low U at graduation	Difference
	1–3 Years after Graduation		
Mean Log annual income	9.32	9.411	-0.091**
	(0.686)	(0.661)	[0.039]
Mean Log hourly wage	1.634	1.801	-0.167***
	(0.432)	(0.475)	[0.027]
Weeks worked in a year	48.514	47.761	0.753
	(8.334)	(9.909)	[0.526]
Proportion of employed	0.896	0.88	0.016
	—	—	[0.016]
Proportion of full-time jobs	0.808	0.807	0.001
	—	—	[0.021]
Mean hours worked per week	44.607	44.44	0.167
(conditioning on full-time jobs)	(7.903)	(8.303)	[0.47]
	4–6 Years after Graduation		
Mean Log annual income	9.72	9.745	-0.025
	(0.503)	(0.482)	[0.029]
Mean Log hourly wage	1.919	1.95	-0.031
	(0.474)	(0.422)	[0.027]
Weeks worked in a year	50.049	50.244	-0.195
	(6.387)	(6.011)	[0.359]
Proportion of employed	0.945	0.923	0.022
	—	—	[0.013]
Proportion of full-time jobs	0.897	0.878	0.019
	—	—	[0.017]
Mean hours worked per week	46.356	45.923	0.433
(conditioning on full-time jobs)	(8.359)	(9.814)	[0.511]
	7–10 Years after Graduation		
Mean Log annual income	9.834	9.849	-0.015
	(0.582)	(0.566)	[0.032]
Mean Log hourly wage	2.057	2.109	-0.052*
	(0.495)	(0.537)	[0.031]
Weeks worked in a year	50.162	49.998	0.164
	(6.065)	(6.88)	[0.358]
Proportion of employed	0.951	0.932	0.019*
	—	—	[0.012]
Proportion of full-time jobs	0.919	0.89	0.029**
	—	—	[0.015]
Mean hours worked per week	47.022	46.557	0.465
(conditioning on full-time jobs)	(9.169)	(9.695)	[0.495]

[1] Standard deviations are in the parentheses, and standard errors for mean comparisons are in the brackets.
[2] ***, ** and *: Significant at the 1, 5 and 10 percent level
[3] Statistics are weighted by the custom weights of workers who were interviewed for personality traits. See Table 19 for unweighted comparisons.

Table 2.8: Log Annual Income as a Function of Entry Conditions and Traits

	Log Annual Income			
	(1)	(2)	(3)	(4)
U_c	-0.045	-0.045^{*}	-0.047^{**}	-0.046^{***}
	(0.027)	(0.026)	(0.020)	(0.015)
U_c x PE	0.003	0.004	0.004	0.004
	(0.003)	(0.004)	(0.004)	(0.003)
AFQT	0.103^{***}	0.108^{***}	0.114^{***}	0.075^{**}
	(0.028)	(0.030)	(0.030)	(0.037)
AFQT x U_c			-0.007	0.017
			(0.017)	(0.037)
AFQT x PE				0.010^{*}
				(0.006)
AFQT x U_c x PE				-0.006
				(0.007)
O		-0.003	0.003	-0.010
		(0.025)	(0.025)	(0.030)
O x U_c			0.020	0.031
			(0.028)	(0.028)
O x PE				0.003
				(0.004)
O x U_c x PE				-0.003
				(0.004)
C		0.072^{***}	0.076^{***}	0.129^{***}
		(0.026)	(0.015)	(0.025)
C x U_c			0.041^{**}	0.064^{***}
			(0.018)	(0.012)
C x PE				-0.012^{***}
				(0.004)
C x U_c x PE				-0.005
				(0.003)
E		0.034	0.034	0.019
		(0.029)	(0.028)	(0.036)
E x U_c			0.019	0.029
			(0.023)	(0.027)
E x PE				0.004
				(0.004)
E x U_c x PE				-0.003
				(0.002)
A		-0.025	-0.031	-0.004
		(0.023)	(0.020)	(0.025)
A x U_c			0.004	-0.008
			(0.015)	(0.022)
A x PE				-0.007
				(0.007)
A x U_c x PE				0.003
				(0.004)
N		0.015	0.009	0.006
		(0.035)	(0.036)	(0.041)
N x U_c			-0.004	0.011
			(0.029)	(0.022)
N x PE				0.001
				(0.003)
N x U_c x PE				-0.003
				(0.004)
Contemp. U	-0.047^{***}	-0.047^{***}	-0.046^{***}	-0.047^{***}
	(0.006)	(0.006)	(0.006)	(0.007)
Observations	3,730	3,730	3,730	3,730
Adjusted R^2	0.147	0.160	0.169	0.173

1. The regressions also control quadratic potential experience, cubic time trend and race. 2. Mean log income is 9.63. 3. OCEAN represent Openness to experience, Conscientiousness, Extraversion, Agreeableness and Emotional stability (opposite to Neuroticism). 4. ***, ** and *: Significant at the 1, 5 and 10 percent level. 5. Standard errors are clustered by graduation year.

Table 2.9: Log Hourly Wage as a Function of Entry Conditions and Traits

	Log Hourly Wage			
	(1)	(2)	(3)	(4)
U_c	-0.063^{***}	-0.064^{***}	-0.065^{***}	-0.064^{***}
	(0.014)	(0.014)	(0.013)	(0.014)
U_c x PE	0.005^{*}	0.005^{*}	0.005^{*}	0.005
	(0.003)	(0.003)	(0.003)	(0.003)
AFQT	0.102^{***}	0.102^{***}	0.106^{***}	0.085^{***}
	(0.022)	(0.023)	(0.022)	(0.022)
AFQT x U_c			-0.014	0.003
			(0.009)	(0.020)
AFQT x PE				0.006
				(0.004)
AFQT x U_c x PE				-0.004
				(0.004)
O		0.015	0.016	0.012
		(0.023)	(0.021)	(0.022)
O x U_c			0.024	0.012
			(0.022)	(0.014)
O x PE				0.001
				(0.003)
O x U_c x PE				0.003
				(0.003)
C		0.037^{***}	0.037^{***}	0.058^{**}
		(0.014)	(0.010)	(0.026)
C x U_c			0.013	0.011
			(0.012)	(0.007)
C x PE				-0.005
				(0.005)
C x U_c x PE				0.001
				(0.003)
E		0.027^{*}	0.027	-0.008
		(0.016)	(0.017)	(0.022)
E x U_c			0.011	0.012
			(0.016)	(0.017)
E x PE				0.008^{***}
				(0.002)
E x U_c x PE				-0.001
				(0.001)
A		-0.029	-0.034^{**}	-0.010
		(0.018)	(0.016)	(0.018)
A x U_c			0.008	-0.013
			(0.013)	(0.016)
A x PE				-0.007^{*}
				(0.003)
A x U_c x PE				0.005^{***}
				(0.002)
N		0.028	0.025	-0.004
		(0.024)	(0.025)	(0.038)
N x U_c			0.006	0.023
			(0.022)	(0.020)
N x PE				0.007
				(0.005)
N x U_c x PE				-0.004
				(0.003)
Contemp. U	-0.036^{***}	-0.035^{***}	-0.035^{***}	-0.036^{***}
	(0.011)	(0.011)	(0.011)	(0.011)
Observations	3,433	3,433	3,433	3,433
Adjusted R^2	0.137	0.149	0.157	0.160

1. The regressions also control quadratic potential experience, cubic time trend and race. 2. Mean log hourly wage is 1.90. 3. OCEAN represent Openness to experience, Conscientiousness, Extraversion, Agreeableness and Emotional stability (opposite to Neuroticism). 4. ***, ** and *: Significant at the 1, 5 and 10 percent level. 5. Standard errors are clustered by graduation year.

Table 2.10: Annual Weeks Worked as a Function of Entry Conditions and Traits

	Annual Weeks Worked			
	(1)	(2)	(3)	(4)
U_c	−0.245	−0.269	−0.266	−0.226
	(0.340)	(0.327)	(0.298)	(0.238)
U_c x PE	0.070	0.075	0.072	0.065*
	(0.047)	(0.049)	(0.050)	(0.038)
AFQT	0.341	0.327	0.343	−0.359
	(0.228)	(0.235)	(0.242)	(0.389)
AFQT x U_c			0.111	0.151
			(0.158)	(0.310)
AFQT x PE				0.169**
				(0.068)
AFQT x U_c x PE				−0.018
				(0.056)
O		−0.149	−0.140	−0.395
		(0.229)	(0.222)	(0.290)
O x U_c			−0.170	−0.172
			(0.156)	(0.255)
O x PE				0.061
				(0.054)
O x U_c x PE				−0.001
				(0.042)
C		0.441***	0.443***	0.769*
		(0.167)	(0.157)	(0.419)
C x U_c			0.186*	0.420*
			(0.104)	(0.226)
C x PE				−0.074
				(0.092)
C x U_c x PE				−0.052
				(0.045)
E		0.107	0.099	0.300
		(0.211)	(0.199)	(0.347)
E x U_c			0.141	0.317
			(0.126)	(0.206)
E x PE				−0.048
				(0.050)
E x U_c x PE				−0.040
				(0.035)
A		−0.034	−0.040	0.423
		(0.114)	(0.105)	(0.330)
A x U_c			0.107	0.207
			(0.079)	(0.129)
A x PE				−0.109
				(0.080)
A x U_c x PE				−0.018
				(0.025)
N		0.237	0.235	0.077
		(0.270)	(0.270)	(0.587)
N x U_c			−0.080	−0.101
			(0.204)	(0.536)
N x PE				0.032
				(0.083)
N x U_c x PE				0.002
				(0.079)
Contemp. U	0.017	0.020	0.016	0.019
	(0.130)	(0.127)	(0.128)	(0.125)
Observations	3,730	3,730	3,730	3,730
Adjusted R^2	0.025	0.028	0.028	0.031

1. The regressions also control quadratic potential experience, cubic time trend and race. 2. Mean annual weeks worked are 49.42. 3. OCEAN represent Openness to experience, Conscientiousness, Extraversion, Agreeableness and Emotional stability (opposite to Neuroticism). 4. ***, ** and *: Significant at the 1, 5 and 10 percent level. 5. Standard errors are clustered by graduation year.

Table 2.11: Employment as a Function of Entry Conditions and Traits

	Probability of Being Employed			
	(1)	(2)	(3)	(4)
U_c	−0.004	−0.004	−0.005	−0.004
	(0.009)	(0.009)	(0.009)	(0.009)
U_c x PE	0.002*	0.002**	0.002**	0.002
	(0.001)	(0.001)	(0.001)	(0.001)
AFQT	0.002	0.004	0.004	−0.003
	(0.011)	(0.013)	(0.013)	(0.015)
AFQT x U_c			−0.003	−0.016*
			(0.007)	(0.009)
AFQT x PE				0.002
				(0.002)
AFQT x U_c x PE				0.003**
				(0.001)
O		−0.010	−0.010	−0.005
		(0.010)	(0.010)	(0.010)
O x U_c			−0.007	−0.017**
			(0.007)	(0.007)
O x PE				−0.001*
				(0.001)
O x U_c x PE				0.003***
				(0.001)
C		0.021***	0.019**	0.025***
		(0.007)	(0.008)	(0.009)
C x U_c			−0.000	0.005
			(0.006)	(0.004)
C x PE				−0.001
				(0.002)
C x U_c x PE				−0.001
				(0.001)
E		0.004	0.005	0.024*
		(0.010)	(0.010)	(0.014)
E x U_c			0.012**	0.024**
			(0.006)	(0.010)
E x PE				−0.004***
				(0.002)
E x U_c x PE				−0.003**
				(0.001)
A		0.009	0.009	0.016
		(0.009)	(0.009)	(0.013)
A x U_c			0.005	0.004
			(0.004)	(0.007)
A x PE				−0.002
				(0.001)
A x U_c x PE				0.000
				(0.001)
N		−0.003	−0.003	−0.015
		(0.006)	(0.006)	(0.012)
N x U_c			0.004	0.008
			(0.007)	(0.009)
N x PE				0.003
				(0.002)
N x U_c x PE				−0.001
				(0.001)
Contemp. UE	−0.002	−0.002	−0.002	−0.001
	(0.005)	(0.004)	(0.004)	(0.004)
Observations	4,550	4,550	4,550	4,550
Adjusted R^2	0.015	0.019	0.021	0.024

1. The regressions also control quadratic potential experience, cubic time trend and race. 2. Mean probability of being employed is 0.919. 3. OCEAN represent Openness to experience, Conscientiousness, Extraversion, Agreeableness and Emotional stability (opposite to Neuroticism). 4. ***, ** and *: Significant at the 1, 5 and 10 percent level. 5. Standard errors are clustered by graduation year.

Table 2.12: Full-time Employment as a Function of Entry Conditions and Traits

	Probability of Full-time Jobs			
	(1)	(2)	(3)	(4)
U_c	-0.021^{***}	-0.023^{***}	-0.024^{***}	-0.022^{***}
	(0.008)	(0.008)	(0.008)	(0.008)
U_c x PE	0.005^{***}	0.005^{***}	0.005^{***}	0.005^{***}
	(0.001)	(0.001)	(0.001)	(0.002)
AFQT	0.005	0.004	0.005	-0.013
	(0.009)	(0.011)	(0.011)	(0.013)
AFQT x U_c			0.003	-0.013^{*}
			(0.005)	(0.007)
AFQT x PE				0.004^{***}
				(0.001)
AFQT x U_c x PE				0.004^{***}
				(0.001)
O		-0.016	-0.015	0.002
		(0.012)	(0.012)	(0.017)
O x U_c			-0.000	0.003
			(0.010)	(0.013)
O x PE				-0.004^{**}
				(0.002)
O x U_c x PE				-0.001
				(0.001)
C		0.024^{*}	0.024^{**}	0.044^{***}
		(0.013)	(0.012)	(0.017)
C x U_c			0.009	0.024^{***}
			(0.006)	(0.004)
C x PE				-0.004^{*}
				(0.003)
C x U_c x PE				-0.003^{**}
				(0.001)
E		0.002	0.002	0.016
		(0.013)	(0.013)	(0.016)
E x U_c			0.009	0.016
			(0.009)	(0.012)
E x PE				-0.003
				(0.002)
E x U_c x PE				-0.002
				(0.002)
A		0.002	0.001	0.006
		(0.009)	(0.009)	(0.010)
A x U_c			0.001	-0.000
			(0.004)	(0.008)
A x PE				-0.001
				(0.002)
A x U_c x PE				0.000
				(0.001)
N		0.009	0.008	0.004
		(0.007)	(0.007)	(0.013)
N x U_c			0.003	0.001
			(0.008)	(0.013)
N x PE				0.001
				(0.003)
N x U_c x PE				0.000
				(0.002)
Contemp. U	-0.009	-0.009	-0.009	-0.009
	(0.007)	(0.007)	(0.007)	(0.007)
Observations	4,550	4,550	4,550	4,550
Adjusted R^2	0.023	0.028	0.029	0.033

1. The regressions also control quadratic potential experience, cubic time trend and race. 2. Mean probability of having full-time jobs is 0.866. 3. OCEAN represent Openness to experience, Conscientiousness, Extraversion, Agreeableness and Emotional stability (opposite to Neuroticism). 4. ***, ** and *: Significant at the 1, 5 and 10 percent level. 5. Standard errors are clustered by graduation year.

Table 2.13: Hours Worked per Week as a Function of Entry Conditions and Traits

	Hours Worked Per Week for Full-time jobs			
	(1)	(2)	(3)	(4)
U_c	0.525***	0.558***	0.537**	0.476**
	(0.186)	(0.201)	(0.215)	(0.222)
U_c x PE	−0.048	−0.051	−0.044	−0.031
	(0.043)	(0.046)	(0.048)	(0.048)
AFQT	−0.239	−0.104	−0.068	−0.232
	(0.532)	(0.453)	(0.457)	(0.412)
AFQT x U_c			0.045	0.277
			(0.162)	(0.375)
AFQT x PE				0.038
				(0.079)
AFQT x U_c x PE				−0.057
				(0.087)
O		0.306	0.385**	0.371
		(0.213)	(0.177)	(0.282)
O x U_c			0.296***	0.391**
			(0.098)	(0.175)
O x PE				0.003
				(0.057)
O x U_c x PE				−0.021
				(0.044)
C		0.122	0.251	0.063
		(0.353)	(0.281)	(0.268)
C x U_c			0.492**	−0.035
			(0.232)	(0.162)
C x PE				0.033
				(0.081)
C x U_c x PE				0.121***
				(0.045)
E		0.284	0.229	0.650*
		(0.346)	(0.324)	(0.365)
E x U_c			−0.207*	−0.115
			(0.112)	(0.228)
E x PE				−0.098**
				(0.048)
E x U_c x PE				−0.018
				(0.036)
A		−0.251	−0.308	−0.222
		(0.361)	(0.324)	(0.251)
A x U_c			0.068	−0.015
			(0.285)	(0.275)
A x PE				−0.023
				(0.067)
A x U_c x PE				0.019
				(0.035)
N		−0.361	−0.390	−0.587
		(0.551)	(0.542)	(0.567)
N x U_c			−0.398**	0.258
			(0.165)	(0.273)
N x PE				0.056
				(0.077)
N x U_c x PE				−0.152**
				(0.074)
Contemp. U	−0.223*	−0.224*	−0.229*	−0.217*
	(0.120)	(0.121)	(0.120)	(0.120)
Observations	3,942	3,942	3,942	3,942
Adjusted R^2	0.026	0.029	0.032	0.033

1. The regressions also control quadratic potential experience, cubic time trend and race. 2. Full-time workers work 45.68 hours per week on average. 3. OCEAN represent Openness to experience, Conscientiousness, Extraversion, Agreeableness and Emotional stability (opposite to Neuroticism). 4. ***, ** and *: Significant at the 1, 5 and 10 percent level. 5. Standard errors are clustered by graduation year.

Figures

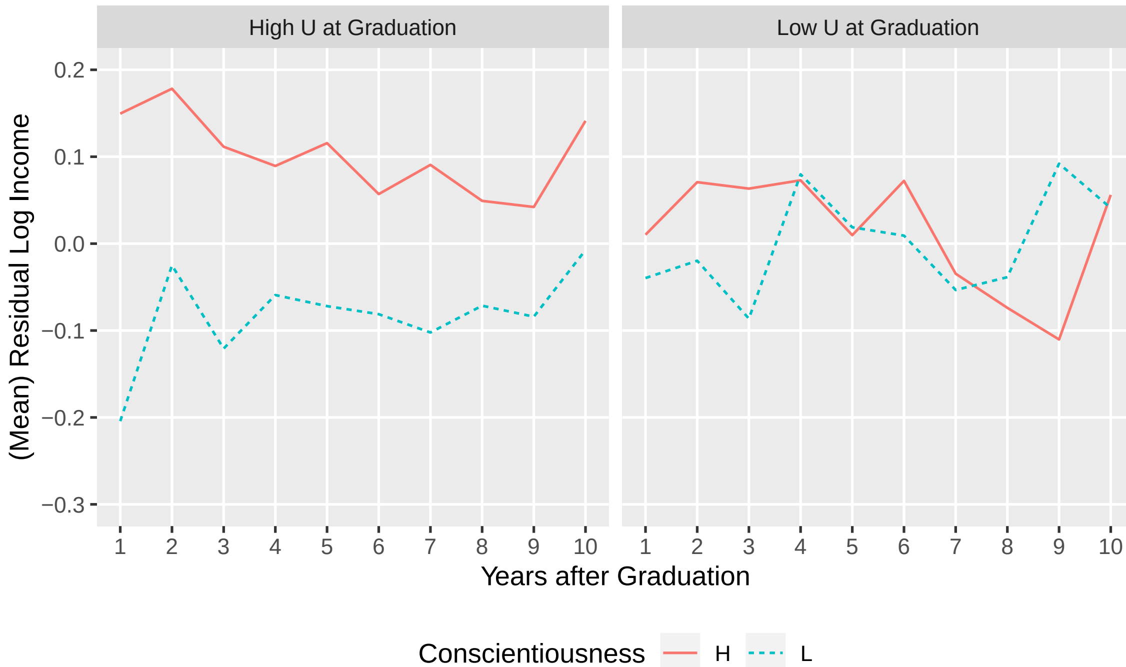


Figure 2.1: Residual Log Annual Income

Notes:

1 The figure plots residual log annual incomes after controlling for labor market conditions at graduation, quadratic potential experience, year fixed effects and race. I use the annual national unemployment rate at graduation to measure labor market conditions at graduation.

2 The figure is based on income observations which are larger than 100 dollars in 1979 value. In addition, I exclude workers who are enrolled on May 01 of the same year.

3 The unemployment rate at graduation is high if the rate is higher than median unemployment rate at graduation. Otherwise the unemployment rate is low.

4 The Conscientiousness score is high if it is higher than the median Conscientiousness score. Otherwise, the Conscientiousness score is low.

3 The means are unweighted.

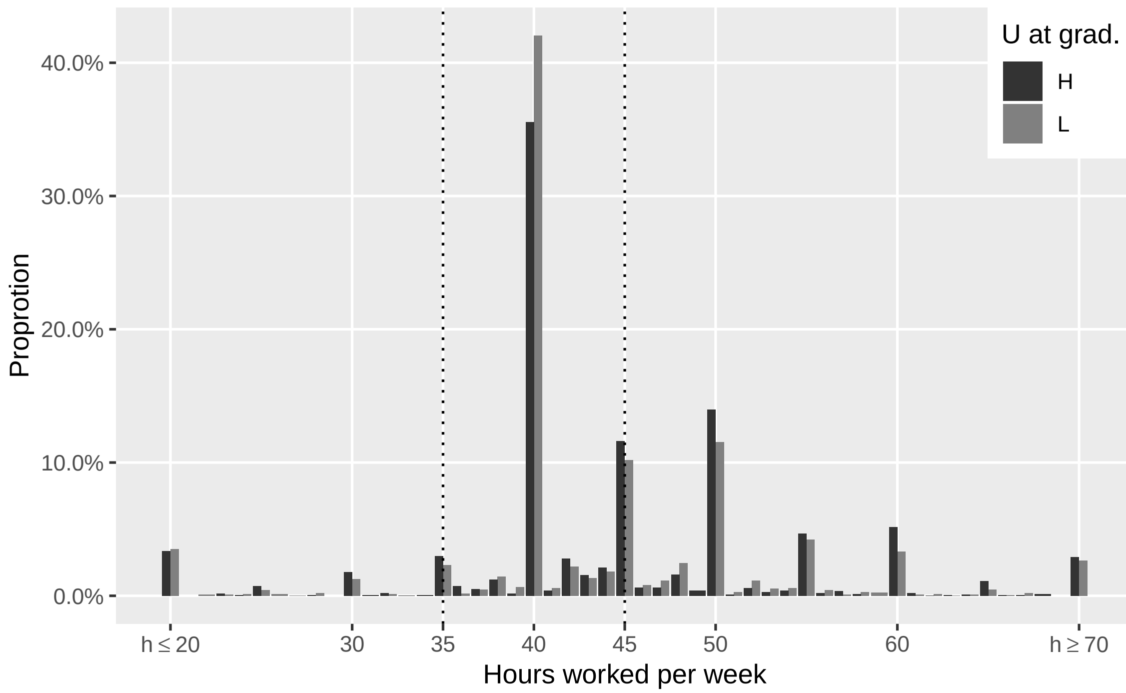


Figure 2.2: Distribution of Weekly Working Hours

Notes:

1 The unemployment at graduation is high if it is higher than the median unemployment rate at the graduation (7.2). Otherwise, the unemployment rate is low.

2 The figure includes observations of weekly working hours in 1–10 years after graduation.

3 The distribution is weighted by the custom weights of workers who were interviewed for personality traits. Figure 9 in the appendix plots the unweighted distribution of hours worked per week.

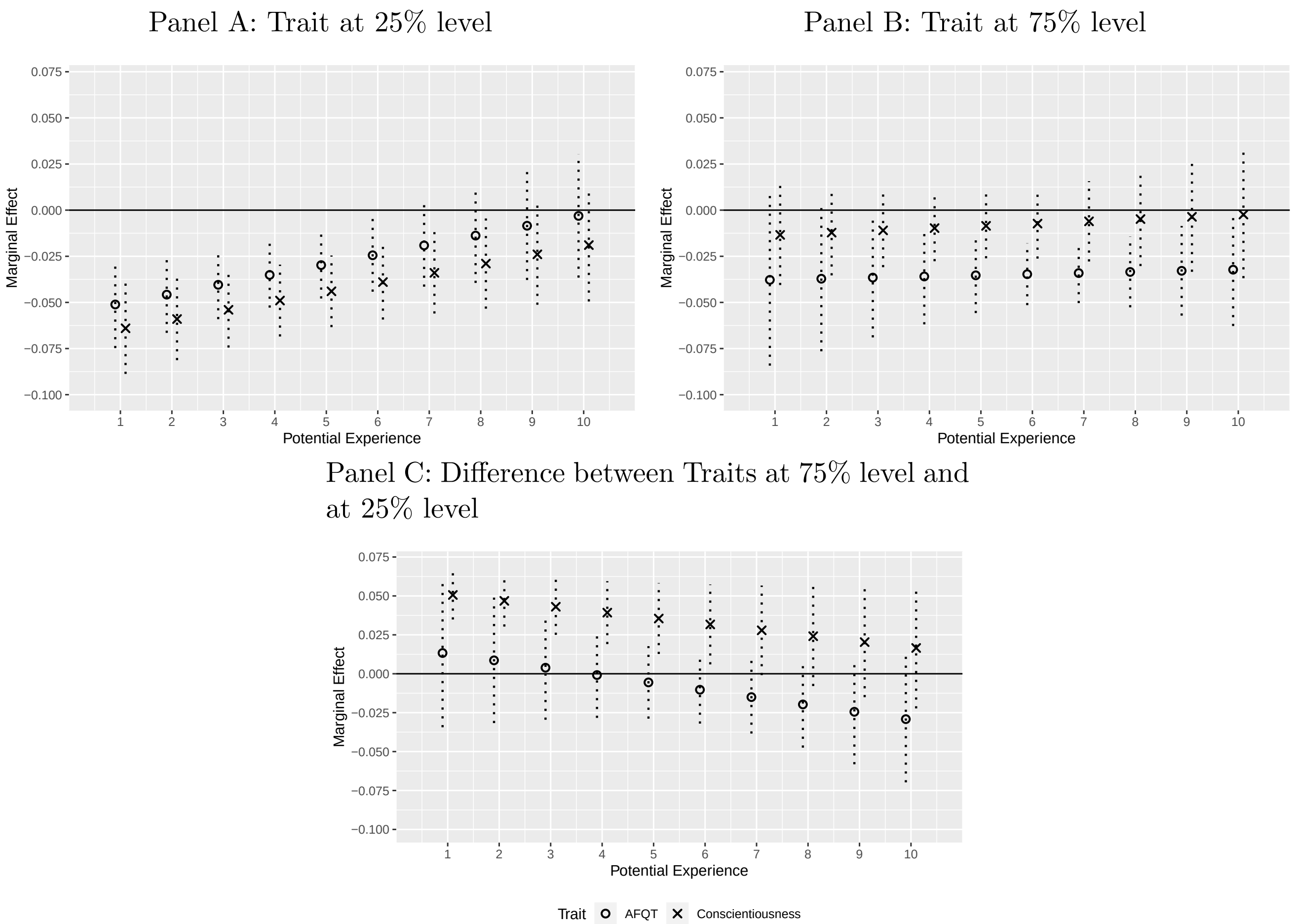


Figure 2.3: Mitigation Effects of Conscientiousness and AFQT on Log Annual Income

Notes: 1. Panel A plots the marginal effects of the unemployment rate at graduation for a worker whose Conscientiousness (AFQT) is at the 25% level and other traits are at the mean levels. 2. Panel B plots the marginal effects of the unemployment rate at graduation for a worker whose Conscientiousness (AFQT) is at the 75% level and other traits are at the mean levels. 3. Panel C compares the difference between Panel B and Panel A. 4. The dotted lines are 90% confidence intervals.

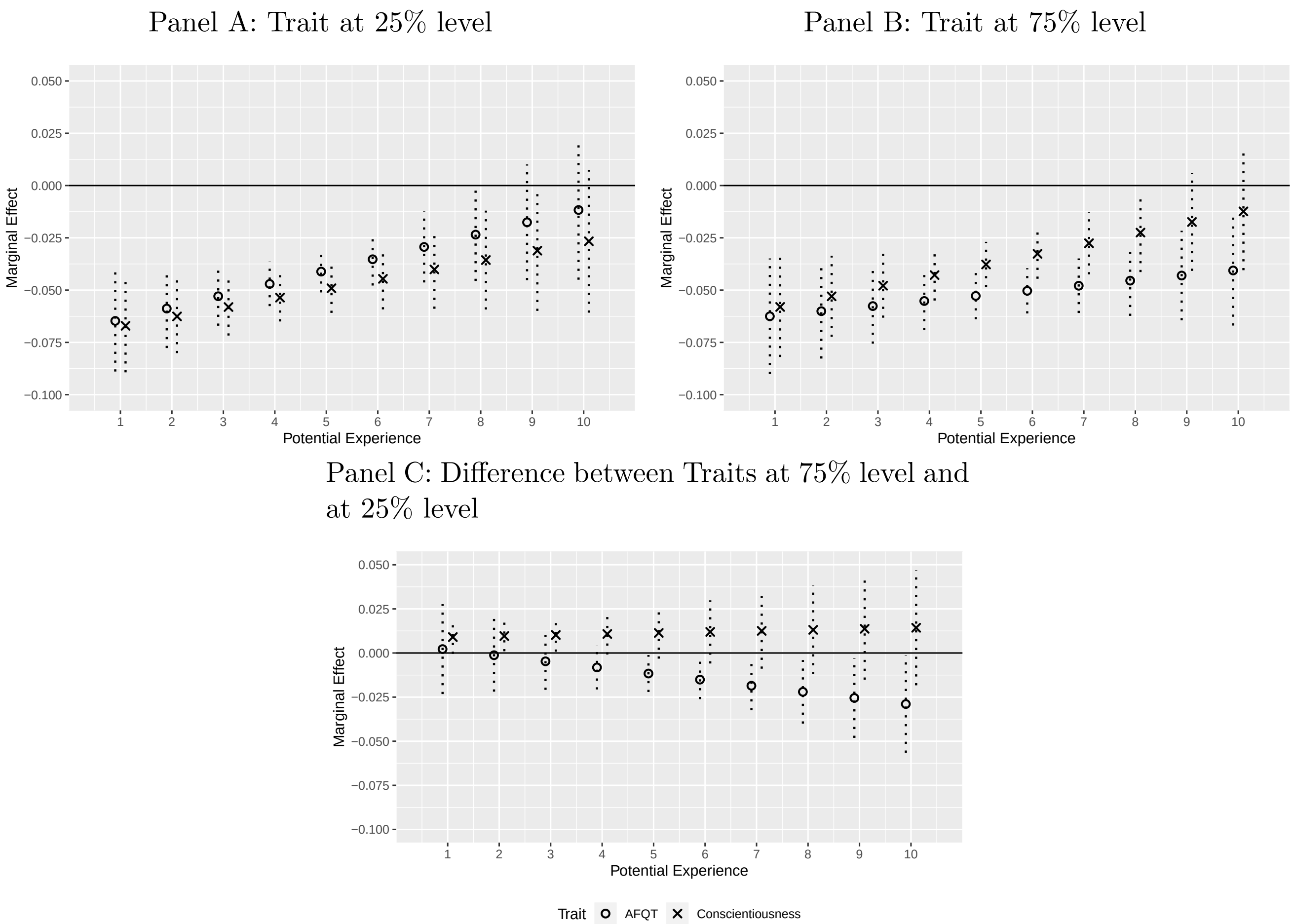
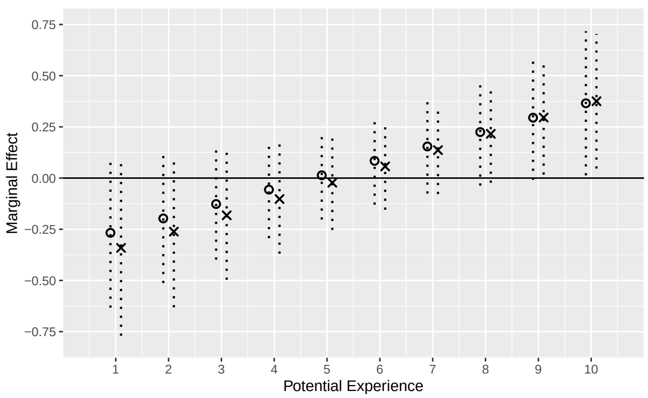


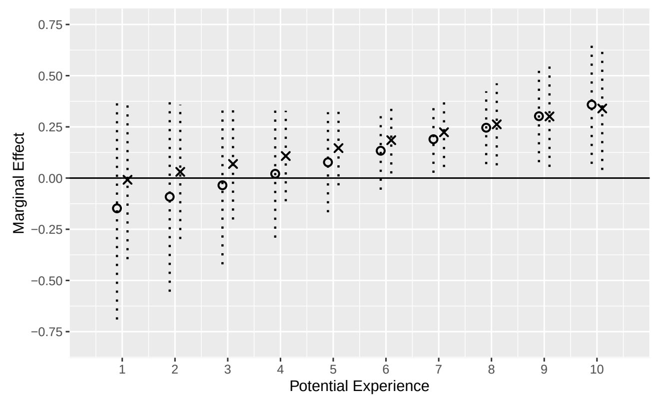
Figure 2.4: Mitigation Effects of Conscientiousness and AFQT on Log Hourly Wage

Notes: 1. Panel A plots the marginal effects of the unemployment rate at graduation for a worker whose Conscientiousness (AFQT) is at the 25% level and other traits are at the mean levels. 2. Panel B plots the marginal effects of the unemployment rate at graduation for a worker whose Conscientiousness (AFQT) is at the 75% level and other traits are at the mean levels. 3. Panel C compares the difference between Panel B and Panel A. 4. The dotted lines are 90% confidence intervals.

Panel A: Trait at 25% level



Panel B: Trait at 75% level



Panel C: Difference between Traits at 75% level and at 25% level

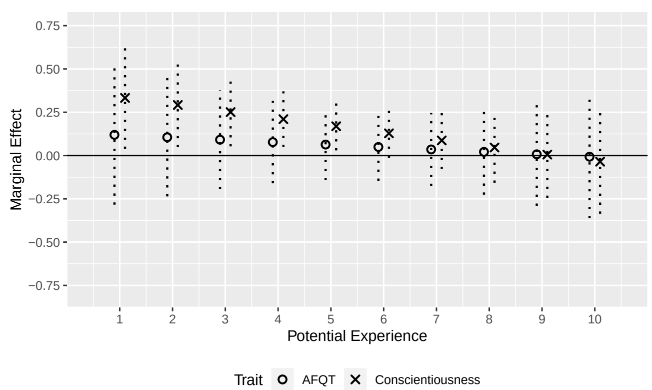


Figure 2.5: Mitigation Effects of Conscientiousness and AFQT on Annual Weeks Worked

Notes: 1. Panel A plots the marginal effects of the unemployment rate at graduation for a worker whose Conscientiousness (AFQT) is at the 25% level and other traits are at the mean levels. 2. Panel B plots the marginal effects of the unemployment rate at graduation for a worker whose Conscientiousness (AFQT) is at the 75% level and other traits are at the mean levels. 3. Panel C compares the difference between Panel B and Panel A. 4. The dotted lines are 90% confidence intervals.

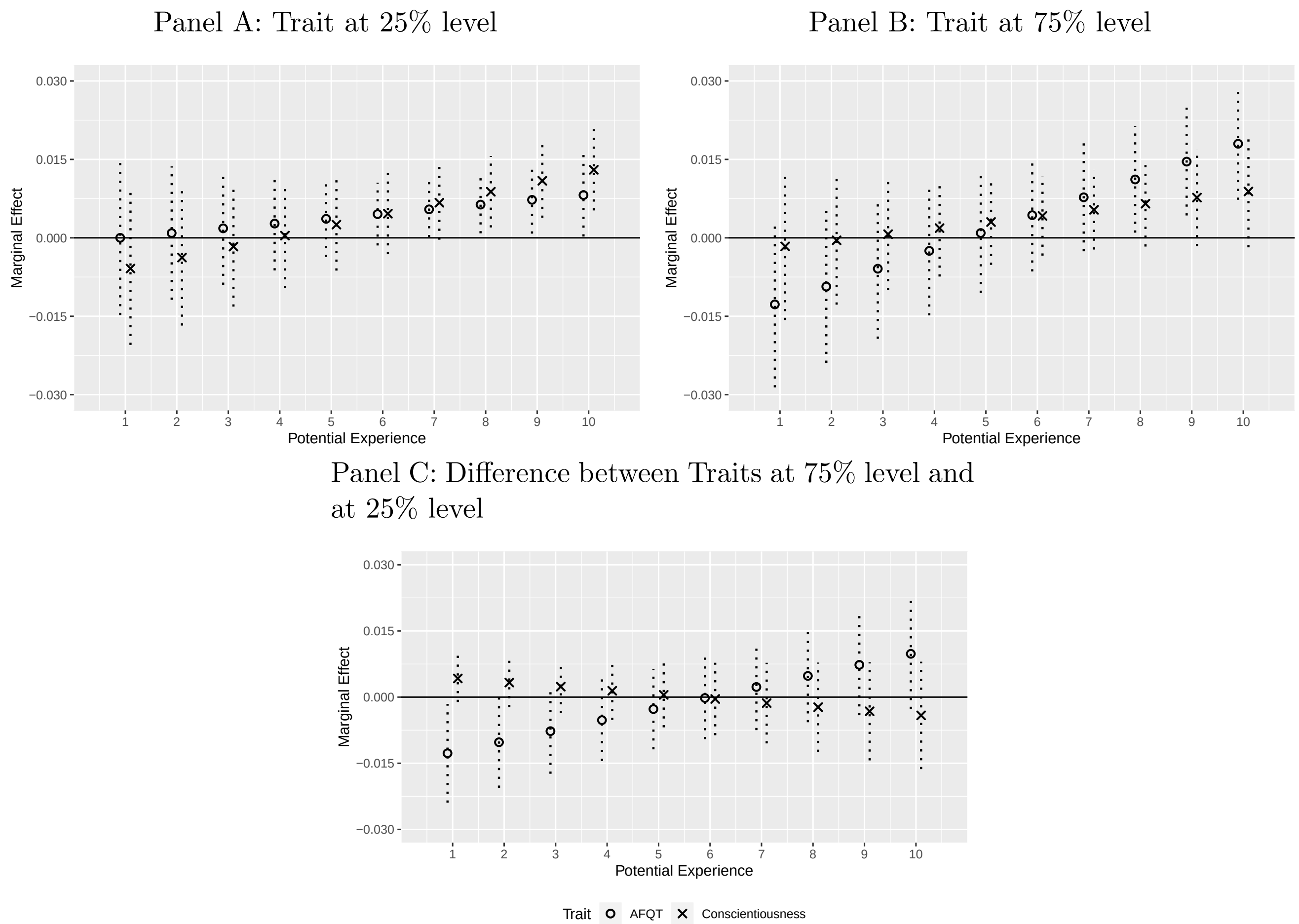


Figure 2.6: Mitigation Effects of Conscientiousness and AFQT on the Probability of Being Employed

Notes: 1. Panel A plots the marginal effects of the unemployment rate at graduation for a worker whose Conscientiousness (AFQT) is at the 25% level and other traits are at the mean levels. 2. Panel B plots the marginal effects of the unemployment rate at graduation for a worker whose Conscientiousness (AFQT) is at the 75% level and other traits are at the mean levels. 3. Panel C compares the difference between Panel B and Panel A. 4. The dotted lines are 90% confidence intervals.

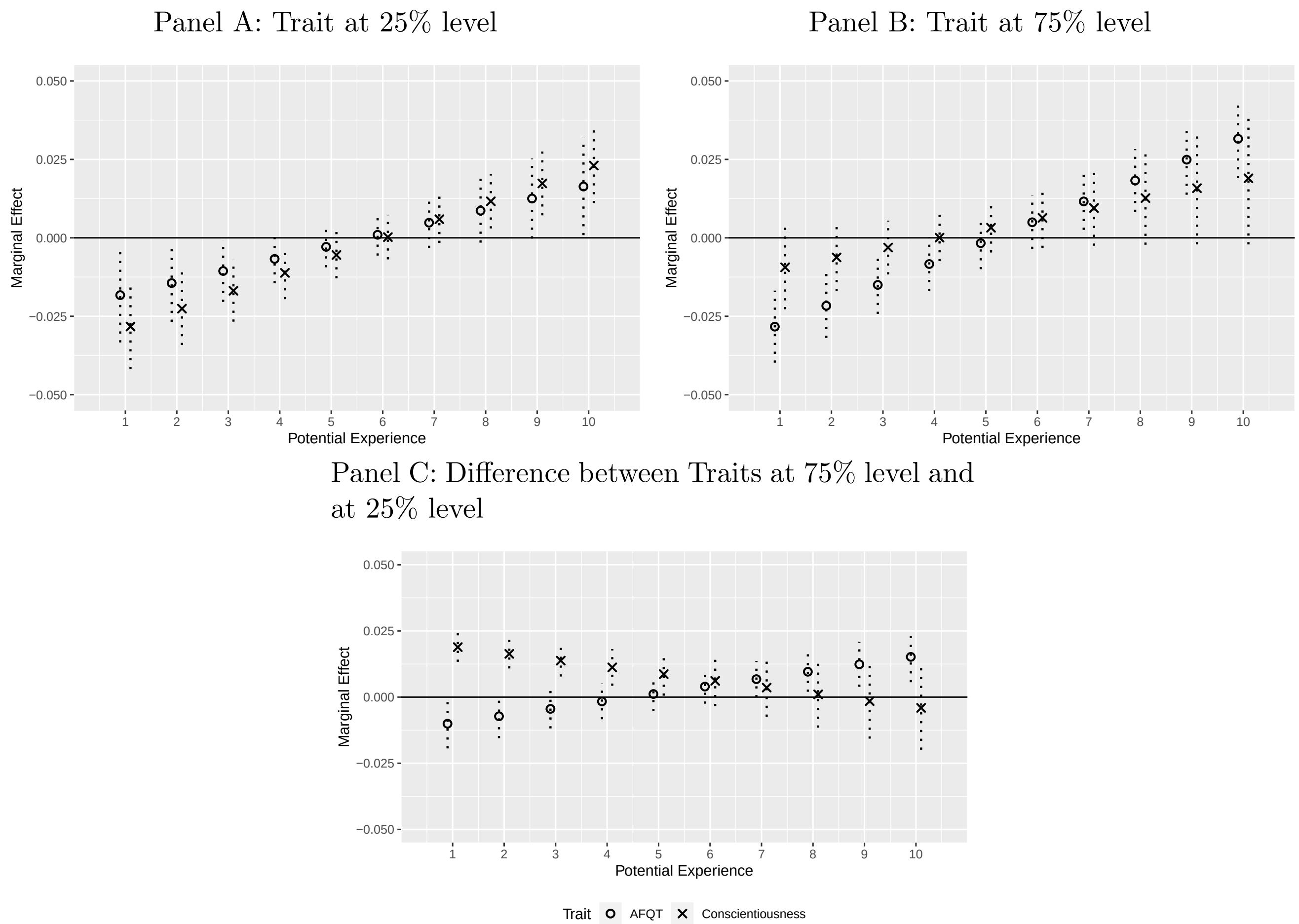
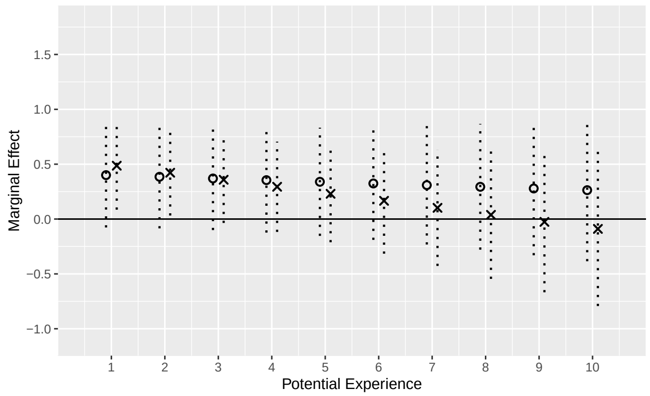


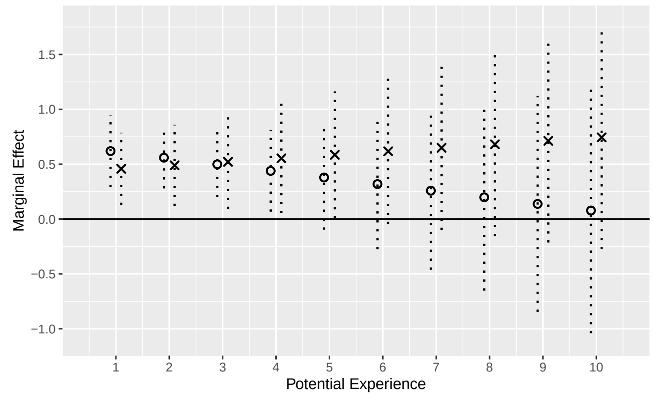
Figure 2.7: Mitigation Effects of Conscientiousness and AFQT on the Probability of Having Full-time Jobs

Notes: 1. Panel A plots the marginal effects of the unemployment rate at graduation for a worker whose Conscientiousness (AFQT) is at the 25% level and other traits are at the mean levels. 2. Panel B plots the marginal effects of the unemployment rate at graduation for a worker whose Conscientiousness (AFQT) is at the 75% level and other traits are at the mean levels. 3. Panel C compares the difference between Panel B and Panel A. 4. The dotted lines are 90% confidence intervals.

Panel A: Trait at 25% level



Panel B: Trait at 75% level



Panel C: Difference between Traits at 75% level and at 25% level

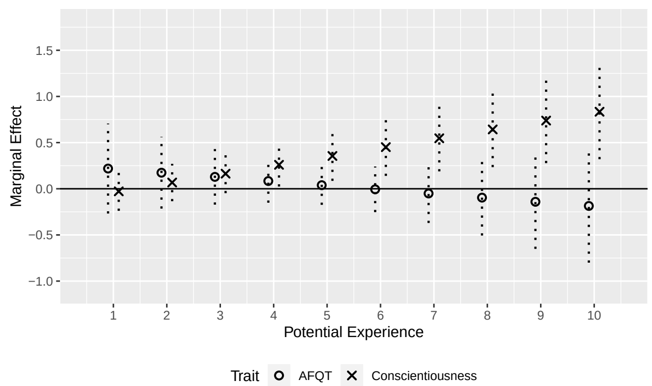


Figure 2.8: Mitigation effects of Conscientiousness and AFQT on hours worked per week for full-time workers

Notes: 1. Panel A plots the marginal effects of the unemployment rate at graduation for a worker whose Conscientiousness (AFQT) is at the 25% level and other traits are at the mean levels. 2. Panel B plots the marginal effects of the unemployment rate at graduation for a worker whose Conscientiousness (AFQT) is at the 75% level and other traits are at the mean levels. 3. Panel C compares the difference between Panel B and Panel A. 4. The dotted lines are 90% confidence intervals.

Appendices

Appendix A Modifications of Occupational Codes

This appendix summarizes the changes due to the modification of occupational codes in Chapter 1. As what I describe in the main paper, I follow Guvenen et al. (2020)'s strategy and assign the occupation that is most often observed in a job spell to that job. Table 14 lists ten three-digit occupations where most of the modifications occur. Among them, managers and administrators (n.e.c.) has the most modifications.

Table 14: Ten Three-digit Occupations with Most Modifications

Occupation Code 1970		Original Occ.		Modified Occ.		
Code	Title	Broad Occ.	Observation	Blue	Pink	White
245	Managers and administrators, n.e.c.	White	143	76	67	—
280	Salesmen and sales clerks, n.e.c.	Pink	52	21	—	31
381	Stock clerks and storekeepers	Pink	51	35	—	16
762	Stockhandlers	Blue	51	—	37	14
374	Shipping and receiving clerks	Pink	42	33	—	9
231	Sales managers and department heads, retail trade	White	36	6	30	—
220	Office managers, n.e.c.	White	30	2	28	—
001	Accountants	White	23	1	22	—
903	Janitors and sextons	Pink	23	21	—	2
202	Bank officers and financial managers	White	21	—	21	—

Note:
[1] n.e.c. represents "not elsewhere classified".

Table 15 compares the number of observations in three broad occupations before and after the modification. There are 2% percentage points fewer of annual job observations in white-collar occupations after the modification. Young workers tend to misreport their occupations as white-collar occupations.

Table 15: Annual Job Observations by Three Broad Occupations before and after the Modification

Occupation	Before modification		After modification	
	Number	Percentage	Number	Percentage
Blue-collar	5002	0.425	5119	0.435
Pink-collar	5344	0.454	5474	0.465
White-collar	1424	0.121	1177	0.100

Note:
[1] 1049 annual job observations change occupations after the correction.

Appendix B The Effects of the Distance between Occupation-specific Productivities on the Return Mobility

This appendix discusses how the distance between a worker's estimated productivities in the occupation which she left ("home" occupation) and the one which she will move to ("destination" occupation) affects her probability of returning to the "home" occupation. The measurement of the distance here is different from the measurement for the strength of a worker's comparative advantage in the main paper. Although both of them measure a worker's productivity distribution, the former one depends on the pair of occupations involved in a change, while the latter one is constant over time for a worker.

The effects of the distance on a worker's probability of returning provide additional evidence on how the productivity distribution interacts with the learning process. A worker who moves to a worse occupation, which she thought was better, is more likely to learn that the "home" occupation is better after observing her output in other occupations. Therefore, she is more likely to return to the "home" occupation. A negative distance here means that her productivity in the "destination" occupation is lower than the "home" occupation, while a positive distance means that her productivity in the "destination" occupation is higher than the "home" one.

Table 16 reports the distance between estimated productivities in the "home" occupation and the "destination" occupation by whether a worker returns or not in three years after her occupational change. Each observation in the table starts with a worker's occupational change and follows her career in the next three years since the change. I restrict changes in the first seven years of a worker's career so that I can observe whether she returns in the next three years or not, as my sample only has job observations in the first ten years of her career. Consistent with the return mobility by potential experience in Table 1.3, there are 36.79% of switches where workers return to "home" occupations in the next three years. On average, in observations where workers return in the next three years, they have significantly lower productivities in the "destination" occupations than in the "home" occupations. In contrast, in observations where workers do not return in the next three years, they have significantly higher productivities in the "destination" occupations than in the "home" occupations.

Table 16: Distance between the Productivities in the "Home" Occupation and in the "Destination" Occupation

	Return in Three Years		T Statistic
	Yes	No	($H_0 : \mu_1 = \mu_2$)
Mean	0.28	-0.68	9.56***
S.D.	1.48	1.34	—
T Statistic ($H_0 : \mu = 0$)	-8.87***	4.31***	—
Number of Observations	521	302	—

Notes:

[1] Each observation in the table starts with a worker's occupational change and follows her career in the next three years since the change. The "home" occupation is where the worker left, and the "destination" occupation is the one which she moves to.

[2] I restrict occupational changes in the first seven years of a worker's career so that I can observe whether she returns in the next three years or not, as my sample only has job observations in the first ten years of her career.

[3] The null hypothesis for each t test in the third row is that the group mean of the distances is equal to zero.

[4] The null hypothesis in the last column is that the means of the distances of two groups are equal.

[5] $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Appendix C Unweighted Summary Statistics

This appendix reports the unweighted summary statistics for the personality traits, AFQT, and labor market outcomes discussed in Chapter 2. Most summary statistics are similar to the weighted results.

Table 17: Mean Personality Traits and AFQT of Different Graduation Cohorts (without Weights)

	High U at grad.	Low U at grad.	Difference
Openness	0.169	0.199	-0.03
	(0.811)	(0.945)	[0.08]
Conscientiousness	0.093	0.085	0.008
	(0.798)	(0.917)	[0.078]
Extraversion	0.086	0.027	0.059
	(0.831)	(0.985)	[0.083]
Agreeableness	-0.128	-0.133	0.005
	(0.862)	(0.902)	[0.08]
Emotional stability	0.159	0.242	-0.083
	(0.839)	(0.883)	[0.078]
AFQT	0.803	0.731	0.072
	(0.821)	(0.78)	[0.072]

[1] The unemployment at graduation is classified as high if it is higher than the median unemployment rate at the graduation of 7.2. Otherwise, the unemployment rate is classified as low. "U" represents the unemployment rate.
[2] Weighted results can be found in Table 2.5.
[3] ***, ** and *: Significant at the 1, 5 and 10 percent level
[4] The standard deviations are in parentheses. The standard errors are in brackets.

labeltbl:OutcomesNoWT

Table 18: Unweighted Labor Market Outcomes of Different Gradation Cohorts)

Labor market outcomes	High U at graduation	Low U at graduation	Difference
Mean Log annual income	9.62	9.647	-0.027
	(0.636)	(0.618)	[0.021]
Mean Log hourly wage	1.87	1.928	-0.058***
	(0.49)	(0.491)	[0.017]
Weeks worked in a year	49.541	49.301	0.24
	(7.087)	(7.782)	[0.244]
Proportion of employed	0.924	0.915	0.009
	(0.265)	(0.279)	[0.008]
Proportion of full-time jobs	0.872	0.862	0.01
	(0.334)	(0.345)	[0.01]
Mean hours worked per week	45.927	45.451	0.476*
(conditioning on full-time jobs)	(8.577)	(9.091)	[0.282]

Notes:

[1] Standard deviations are in parentheses, and standard errors for mean comparisons are in brackets.

[2] ***, ** and *: Significant at the 1, 5 and 10 percent level

[3] Weighted results ca been seen in Table 2.6.

[4] The unemployment at graduation is classified as high if it is higher than the median unemployment rate at graduation of 7.2. Otherwise, the unemployment is classified as low.

Table 19: Unweighted Labor Market Outcomes of Different Gradation Cohorts across Years

Labor market outcomes	High U at graduation	Low U at graduation	Difference
	1–3 Years after Graduation		
Mean Log annual income	9.308	9.391	-0.083**
	(0.709)	(0.677)	[0.04]
Mean Log hourly wage	1.633	1.791	-0.158***
	(0.428)	(0.465)	[0.027]
Weeks worked in a year	48.559	47.8	0.759
	(8.283)	(9.559)	[0.519]
Proportion of employed	0.881	0.886	-0.005
	(0.325)	(0.318)	[0.017]
Proportion of full-time jobs	0.798	0.817	-0.019
	(0.402)	(0.387)	[0.021]
Mean hours worked per week	44.253	43.99	0.263
(conditioning on full-time jobs)	(7.858)	(7.554)	[0.448]
	4–6 Years after Graduation		
Mean Log annual income	9.696	9.727	-0.031
	(0.509)	(0.487)	[0.029]
Mean Log hourly wage	1.902	1.933	-0.031
	(0.466)	(0.431)	[0.027]
Weeks worked in a year	49.951	50.367	-0.416
	(6.403)	(5.661)	[0.349]
Proportion of employed	0.943	0.923	0.02
	(0.232)	(0.266)	[0.013]
Proportion of full-time jobs	0.895	0.881	0.014
	(0.307)	(0.325)	[0.017]
Mean hours worked per week	45.959	45.864	0.095
(conditioning on full-time jobs)	(8.123)	(9.65)	[0.505]
	7–10 Years after Graduation		
Mean Log annual income	9.804	9.842	-0.038
	(0.574)	(0.578)	[0.032]
Mean Log hourly wage	2.026	2.098	-0.072**
	(0.483)	(0.537)	[0.03]
Weeks worked in a year	49.984	49.826	0.158
	(6.495)	(7.279)	[0.38]
Proportion of employed	0.943	0.936	0.007
	(0.232)	(0.245)	[0.012]
Proportion of full-time jobs	0.91	0.889	0.021
	(0.286)	(0.314)	[0.015]
Mean hours worked per week	47.018	46.473	0.545
(conditioning on full-time jobs)	(9.174)	(9.702)	[0.494]

[1] Standard deviations are in parentheses, and standard errors for mean comparisons are in brackets.
[2] ***, ** and *: Significant at the 1, 5 and 10 percent level.
[3] Weighted results can be found in Table 2.7.

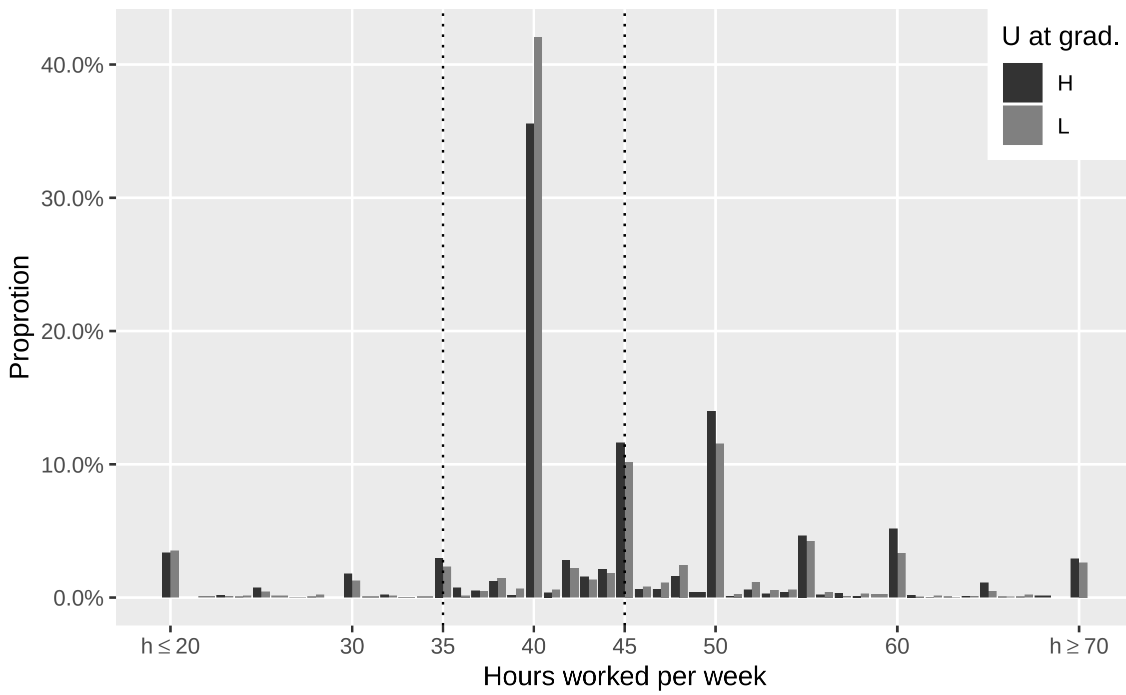


Figure 9: Distribution of Weekly Working Hours (without Weights)

Notes:

1. The unemployment at graduation is high if it is higher than the median unemployment rate at the graduation (7.2). Otherwise, the unemployment rate is low.
2. The figure includes observations of weekly working hours in 1–10 years after graduation.
3. The distribution is unweighted. See Figure 2.2 for the weighted distribution of hours worked per week.

Appendix D Age-adjusted Personality Traits

This appendix discusses the results of using age-adjusted personality traits. I follow the method in Heineck and Anger (2010) and adjust personality traits by regressing each trait on age and age square. Then I use the residuals as the age-adjusted personality traits. Table 20 reports the regressions used to adjust the personality traits. The worker's age at the interview date explains less than 0.1% of the variations of personality traits in the NLSY79. Besides, we cannot reject the null hypothesis that all the coefficients are equal to zero for regressions on Openness, Conscientiousness, and Agreeableness. To sum up, Conscientiousness is not likely to be affected by the age when workers report their personality traits.

Table 20: Effects of Age and Age Square on Personality Traits

	O	C	E	A	N
Age (Year)	0.232	0.195	0.496	−0.158	−0.336
	(0.376)	(0.375)	(0.417)	(0.364)	(0.395)
Age Square / 100	−0.215	−0.176	−0.477	0.154	0.294
	(0.348)	(0.346)	(0.385)	(0.336)	(0.365)
Constant	−1.271	0.354	−8.417	9.226	14.688
	(10.177)	(10.134)	(11.269)	(9.834)	(10.690)
Observations	6,703	6,703	6,703	6,703	6,703
R^2	0.0001	0.0001	0.001	0.0002	0.001
F Statistic (df = 2; 6700)	0.198	0.317	3.929**	0.836	3.259**

Notes:
[1] OCEAN represent Openness to experience, Conscientiousness, Extraversion, Agreeableness and Emotional stability (opposite to Neuroticism).
[2] ***, ** and *: Significant at the 1, 5 and 10 percent level.
[3] The age is measured on the date when personality traits were measured.

I repeat the regressions in the main paper using the age-adjusted personality traits. The results are in Table 21. Both the main effects of entry conditions, AFQT, and Conscientiousness and the mitigation effects of AFQT and Conscientiousness on all labor market outcomes are pretty much the same as the effects discussed in the main paper.

Table 21: Effects of Unemployment Rates at Graduation and Age-adjusted Personality Traits on Labor Market Outcomes

	Log Annual Income	Log Hourly Wage	Annual Weeks worked	Prob. Employed	Prob. Full-time	Hours worked per week
U_c	-0.046^{***}	-0.063^{***}	-0.223	-0.005	-0.022^{***}	0.477^{**}
	(0.015)	(0.014)	(0.234)	(0.008)	(0.008)	(0.218)
U_c x PE	0.004	0.005	0.065^{*}	0.002^{**}	0.005^{***}	-0.026
	(0.003)	(0.003)	(0.038)	(0.001)	(0.002)	(0.050)
AFQT	0.075^{**}	0.085^{***}	-0.361	-0.003	-0.013	-0.235
	(0.037)	(0.022)	(0.389)	(0.009)	(0.013)	(0.412)
AFQT x U_c	0.017	0.003	0.152	-0.016^{***}	-0.013^{*}	0.278
	(0.036)	(0.020)	(0.310)	(0.005)	(0.007)	(0.374)
AFQT x PE	0.010^{*}	0.006	0.170^{**}	0.002^{*}	0.004^{***}	0.038
	(0.006)	(0.004)	(0.068)	(0.001)	(0.001)	(0.079)
AFQT x U_c x PE	-0.006	-0.004	-0.018	0.003^{***}	0.004^{***}	-0.058
	(0.007)	(0.004)	(0.056)	(0.001)	(0.001)	(0.086)
O	-0.011	0.012	-0.413	-0.005	0.002	0.383
	(0.031)	(0.023)	(0.301)	(0.010)	(0.018)	(0.292)
O x U_c	0.033	0.013	-0.180	-0.018^{***}	0.003	0.406^{**}
	(0.029)	(0.015)	(0.263)	(0.005)	(0.013)	(0.180)
O x PE	0.003	0.001	0.064	-0.002^{*}	-0.004^{**}	0.004
	(0.004)	(0.003)	(0.056)	(0.001)	(0.002)	(0.059)
O x U_c x PE	-0.003	0.003	-0.001	0.003^{***}	-0.001	-0.023
	(0.004)	(0.004)	(0.043)	(0.001)	(0.001)	(0.046)
C	0.134^{***}	0.060^{**}	0.789^{*}	0.026^{**}	0.045^{***}	0.059
	(0.026)	(0.027)	(0.436)	(0.010)	(0.017)	(0.276)
C x U_c	0.067^{***}	0.012	0.432^{*}	0.005	0.025^{***}	-0.038
	(0.012)	(0.007)	(0.233)	(0.005)	(0.004)	(0.167)
C x PE	-0.012^{***}	-0.005	-0.075	-0.002	-0.005^{*}	0.037
	(0.004)	(0.006)	(0.096)	(0.001)	(0.003)	(0.083)
C x U_c x PE	-0.005^{*}	0.001	-0.053	-0.001^{*}	-0.003^{**}	0.124^{***}
	(0.003)	(0.003)	(0.047)	(0.001)	(0.001)	(0.046)
E	0.018	-0.007	0.293	0.024^{***}	0.016	0.660^{*}
	(0.036)	(0.022)	(0.334)	(0.008)	(0.016)	(0.366)
E x U_c	0.028	0.012	0.321	0.023^{***}	0.016	-0.103
	(0.027)	(0.017)	(0.205)	(0.006)	(0.012)	(0.227)
E x PE	0.004	0.008^{***}	-0.047	-0.004^{***}	-0.003	-0.104^{**}
	(0.004)	(0.003)	(0.048)	(0.001)	(0.002)	(0.048)
E x U_c x PE	-0.002	-0.001	-0.041	-0.002^{***}	-0.001	-0.021
	(0.002)	(0.001)	(0.035)	(0.001)	(0.002)	(0.036)
A	-0.003	-0.011	0.439	0.017	0.007	-0.239
	(0.026)	(0.018)	(0.335)	(0.015)	(0.010)	(0.258)
A x U_c	-0.008	-0.013	0.208	0.004	-0.000	-0.022
	(0.022)	(0.017)	(0.129)	(0.007)	(0.008)	(0.279)
A x PE	-0.007	-0.007^{*}	-0.113	-0.002	-0.001	-0.019
	(0.007)	(0.004)	(0.081)	(0.001)	(0.002)	(0.070)
A x U_c x PE	0.003	0.006^{***}	-0.018	0.000	0.000	0.021
	(0.004)	(0.002)	(0.026)	(0.001)	(0.001)	(0.036)
N	0.007	-0.004	0.084	-0.016	0.004	-0.584
	(0.042)	(0.039)	(0.597)	(0.016)	(0.014)	(0.579)
N x U_c	0.010	0.022	-0.094	0.009	0.001	0.266
	(0.022)	(0.020)	(0.546)	(0.011)	(0.013)	(0.281)
N x PE	0.000	0.007	0.031	0.003^{*}	0.001	0.051
	(0.003)	(0.005)	(0.084)	(0.002)	(0.003)	(0.079)
N x U_c x PE	-0.003	-0.004	0.002	-0.001	0.000	-0.154^{**}
	(0.004)	(0.003)	(0.081)	(0.001)	(0.002)	(0.076)
Contemp. U	-0.047^{***}	-0.036^{***}	0.018	-0.002	-0.009	-0.218^{*}
	(0.007)	(0.011)	(0.125)	(0.003)	(0.007)	(0.119)
Observations	3,730	3,433	3,730	4,550	4,550	3,942
Adjusted R^2	0.173	0.160	0.031	0.024	0.033	0.033

1. Personality traits are age-adjusted. 2. The regressions also control quadratic potential experience, cubic time trend and race. 3. OCEAN represent Openness to experience, Conscientiousness, Extraversion, Agreeableness and Emotional stability (opposite to Neuroticism). 4. ***, ** and *: Significant at the 1, 5 and 10 percent level. 5. Standard errors are clustered by graduation year.

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