A Dynamic Model of Personality, Schooling, and Occupational Choice

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Abstract

This paper develops a dynamic discrete choice model of schooling and occupational choices that incorporates time-varying personality traits, as measured by the so-called "Big Five" traits. The model is estimated using the HILDA longitudinal dataset from Australia. Personality traits are found to play a critical role in explaining education and occupation choices over the lifecycle. The traits evolve during young adult years but stabilize in the mid-30s. Results show that individuals with a comparative advantage in schooling and white-collar work have, on average, higher cognitive skills and higher personality traits, in all five dimensions. The estimated model is used to evaluate two education policies: compulsory senior secondary school and a 50% college subsidy. Both policies are found to be effective in increasing educational attainment, but the compulsory schooling policy provides greater benefits to lower socioeconomic groups. Allowing personality traits to evolve with age and with years of schooling proves to be important in capturing policy response heterogeneity.

JEL: C54, J24, I24, I28

Keywords: personality traits and education policies, unobserved types, lifetime inequality, dynamic discrete choice

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1 Introduction

It has long been recognized that cognitive skills are important determinants of labor market success, but there is increasing evidence that noncognitive skills also play a salient role.(Becker (1964); Griliches (1977)) For example, using data from the Perry Preschool randomized experiment, Heckman et al. (2010) find that the ability to plan and to exert self-control significantly affects lifetime earnings and employment. Devising effective social policies that maximize the potential for human development requires an understanding of the mechanisms through which cognitive and noncognitive skills evolve and influence individuals' education and labor market trajectories.

This paper develops and estimates a dynamic model of schooling, work, and occupational choices that incorporates noncognitive personality traits, as measured by the so-called "Big Five." Our model allows both cognitive and noncognitive traits to influence educational and labor market outcomes through multiple channels, by affecting pecuniary or nonpecuniary returns from schooling and by affecting the reward from choosing white or blue collar occupations. Our analysis is inspired in part by the pioneering work of Keane and Wolpin (1997) that estimates a similar type of model without personality traits.

A key finding from Keane and Wolpin's (1997) analysis is that 90 percent of the total variance in expected lifetime utility is explained by unobserved skill endowments at age 16. The importance of unobserved heterogeneity in explaining educational and labor market outcomes has also been confirmed in numerous other studies. For example, Yamaguchi (2012) finds that endowment differences prior to labor market entry account for 70% of the log-wage variance in the first year and 35% even after 20 years. Sullivan (2010) finds that 56% of the variance in discounted expected lifetime utility is explained by initial heterogeneity. Huggett et al. (2011) conclude that 61.5 percent of the variation in lifetime earnings and 64.0 percent of the variation in lifetime utility is attributable to initial conditions.

Although accumulated evidence clearly points to the importance of endowment heterogeneity in explaining educational and labor market outcomes, its precise components remain unclear. Keane and Wolpin (1997) find that family background accounts for less than 10 percent of the total variation in lifetime utility and that the addition of cognitive ability only increases the explained variation to 14 percent. Prior studies have not considered the potential role of personality traits as a component of endowment heterogeneity because the datasets typically used do not include repeated personality trait measurements.

In the psychology literature, personality traits have been shown to be correlated with many aspects of individuals' lives. However, study of their effects on economic outcomes is relatively scarce. (Almlund et al. (2011)) The five-factor model (so called "Big-five") is the most widely adopted measurement of personality in both psychology (Goldberg (1992);Saucier (1994);Gosling et al. (2003)) and economics (Borghans et al. (2008)). The Big Five traits include openness to experience, conscientiousness, extraversion, agreeableness and neuroticism (OCEAN). The meaning of these traits and their determination will be further described below.

The model assumes that individuals make one of four mutually exclusive choices among attending school, staying home, working in a white-collar job or working in a blue-collar job from ages 15 to 58. Individual endowments at age 15 consist of personality traits, cognitive ability, and family background characteristics, which include parental schooling, number of siblings, sibling order and whether the person lived with both parents at age 14. To allow for unobserved heterogeneity in a tractable way, we assume each individual is one of four types (denoted I-IV). An individual's type potentially affects their pecuniary and nonpecuniary reward from choosing particular schooling or work options. In the dynamic discrete choice literature, it is common to assume unobserved types are fixed over time (e.g. Keane and Wolpin (1997), Yamaguchi (2012), Sullivan (2010)). Our model begins at age 15 when personality traits are still evolving. We therefore allow the unobserved types, which depend in part on personality traits, to change with age. We find evidence that some types of individuals possess higher dimensions, on average, of all five personality traits. We implement a likelihood ratio test for type stability over the life-cycle, which is usually assumed in other schooling and occupational choice models, which we strongly reject in our data.

The model is estimated using the Household Income and Labour Dynamics in Australia (HILDA) longitudinal data set, waves 1(2001) through 13(2013). The data have repeated measures of the big-five personality traits as well as measures of cognitive ability. Our estimation results show that the unobserved types are malleable at early ages. At age 15, individuals have on average a 40% probability to change type, but by age 36 their type stabilizes. Our estimation results are broadly consistent with findings from some psychology studies on personality trait stability. For example, Terracciano et al. (2006) and Terracciano et al. (2010) report that intra-individual stability increases up to age 30 and thereafter stabilizes.

We use the estimated model to evaluate two education policies: making senior secondary school compulsory and providing a 50% cost subsidy to attend college. Both policies provide incentives to enroll in school but differ in their distributional implications. Individuals belonging to types I and IV are found to have a comparative advantage in education and to receive the most benefit from the college subsidy policy. Their average number of years of completed education increases by around one year, in comparison to half a year on average for types II and III. In contrast, the impacts of compulsory senior second school are concentrated on types II and III, who tend to come from lower SES backgrounds. The average increase in years of education is around one-half for these two types but close to zero for the other two types. Thus, the two policies both increase average years of education but have very different distributional effects.

To study the relevance of personality traits in assessing policy impacts, we also estimate a model with fixed types in which there is no possibility for personality traits to change in response to education policies. When this channel is shut down, we find that there is less incentive for disadvantaged groups to pursue education, because they no longer have the potential to change their disadvantaged types. As a result, the increase in annual earnings attributable to the policy intervention is significantly smaller in the fixed type model. In other words, the inequality in the distribution of the policy effect is significantly overstated in the restricted fixed type model.

This paper is organized as follows: Section II reviews the literature. Section III describes the HILDA data and the measures of "Big-five". Section IV describes the general structure of our model and its econometric implementation. Section V discusses the identification strategy and estimation method. Section VI explains our estimation strategy. Section VII presents the estimation results and provides information for the goodness of model fit. The model implications are discussed in section VIII. Section IX reports results from the two policy experiments and section X concludes.

2 Literature Review

The "Big Five" personality traits are defined as follows: (1) 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; characterized by positive affect and sociability, (2) neuroticism: a chronic level of emotional instability and proneness to psychological distress. Emotional stability is predictability and consistency in emotional reactions, with absence of rapid mood changes, (3) openness to experience/intellect: the tendency to be open to new esthetic, cultural, or intellectual experiences, (4) conscientiousness: the tendency to be organized, responsible, and hardworking and (5) agreeableness: the tendency to act in a cooperative, unselfish manner.

Several studies examine the influence of personality traits on wage performance and occupational choices. For example, both Nyhus and Pons (2005) and Salgado (1997) find that emotional stability and conscientiousness are strongly correlated with wage and job performance. Cubel et al. (2016) examine whether Big Five personality traits affect productivity using data gathered in a laboratory setting where the task effort is directly measurable. They find that individuals who exhibit high levels of conscientiousness and higher emotional stability perform better on the task. Fletcher (2013) uses data on siblings and finds a robust relationship between personality traits and wages using sibling samples. Specifically, conscientiousness, emotional stability, extraversion and openness to experience were all found to positively affect wages. There are few papers that examine the correlation between personality traits and educational attainment. Personality traits are predictive of educational attainment. For example, Lundberg (2013) finds positive correlations between personality traits (such as conscientiousness, agreeableness and openness to experience) and college entrance. However, personality traits may also be changed by education experience. Dahmann and Anger (2014) and Schurer et al. (2015) note that educational experiences in secondary school and at university shape students' personality.

Our paper is also related to the burgeoning literature examining the process of noncognitive skill formation. Heckman et al. (2006) study the effect of non-cognitive skills on schooling decisions and subsequent labour market outcomes, allowing schooling and family background to influence be potential determinants of skill formation. Cunha and Heckman (2008) estimate a linear dynamic model to study the formation of cognitive and non-cognitive skill as it depends on parental investment. Heckman and Raut (2016) formulate a dynamic structural model that integrates preschool investment choices that affect skill formation with schooling and earning outcomes later in life.

3 Data

The analysis is based on a sample of individuals from the Household Income and Labour Dynamics in Australia (HILDA) longitudinal data set. HILDA is a representative one in one thousand sample of the Australian population. It is an ongoing annual dataset starting from the year 2001 with 19,914 initial individuals from 7,682 households. (Summerfield et al. (2014)) Our paper makes use of the variables in the following categories: (1) labor market outcomes including occupational information (coded following the ANZSCO system[1]), annual labor earnings and working hours; (2) family background information including parental education levels, sibling number and order as well as measures of household intactness; (3) education levels ranging from senior secondary school until the highest degree; (4) cognitive ability measured in wave 12; and (5) the "Big-five" personality traits assessment repeatedly collected in wave 5, 9 and 13.

To the best of our knowledge, HILDA has the best quality measures of personality traits among all nationwide data sets. For the majority of respondents, we observe three repeated measurements of personality traits over an eight-years time window.[2] HILDA's "Big-Five" information is based on 36 personality questions.(table 2) Respondents were asked to pick a number between 1 to 7 to assess how well each personality adjective describes them. The lowest number 1 denotes a total opposite description and the highest number 7 denotes a perfect description. According to Losoncz (2009), only 28 of 36 items load well into their corresponding components when performing factor analysis. The other 8 items are discarded due to either their low loading value or their ambiguity on several traits.[3] The construction of "Big-five" in our paper follows the approach of Losoncz (2009). Big-five personality traits are available for 4,938 males aged 15-58

[1]In practice, we classify all occupations into two categories: blue-collar job and white-collar job. White collar jobs includes managers, professionals, technicians and tradesperson. Blue collar jobs include community and personal service workers, clerical and administrative workers, sales workers, machinery operators and drivers as well as labourers. See table 1 for details.

[2]One alternative national-wide data set providing personality traits inventory assessment is German Socio-Economic Panel (GSOEP) study. GSOEP also surveys "Big-five" three times in years 2005, 2009 and 2013. However, since the education system in Germany is significantly different from the North American school model by separating students as early as secondary level depending on academic achievement level and interests. Thus, we focus our attention on HILDA instead.

[3]The way to check each item' loading performance is to calculate the loading value after doing oblimin rotation. The loading values of 8 abandoned items were either lower than 0.45, or did not load more than 1.25 times higher on the expected factor than any other factor.(Losoncz (2009))

interviewed in wave 5. The traits are recorded for is 5,048 and 6,771 respondents in wave 9 and wave 13, respectively. We include all individuals who have at least one measure of personality traits in our estimation sample.[4]

Cognitive ability is only surveyed once in wave 12.[5] We construct a one-dimensional measure of cognitive ability from three different measurements: (i) Backward Digits Span, (ii) Symbol Digits Modalities and (iii) a 25-item version of the National Adult Reading Test.

3.1 Additional background variables and sample restrictions

In addition to the cognitive and noncognitive trait measures described above, we use the following information in our analysis: sibling information (including whether the person has siblings, whether he is the eldest child in the family and how many siblings), an indicator of growing up in an intact family, parental education, and parental working information.[6] We also include state of residence and cohort information.

Our estimation focuses on males between age 15-58. Women are not included to avoid additional complication of modeling marriage and fertility decisions, which may impact schooling and labor supply decisions to a larger extent. We exclude the persons age 58 or older because most people are retired by that age. Individuals serving in the military are also dropped. Lastly, we drop person-year observations that are missing information on the state space variables in our model. The remaining sample has 36,639 observations from 4,215 individuals in total.

Selected summary statistics of individual's characteristics are reported in table 3. Our sample is distributed across eight states and territories.[7] 83.4% of individuals report residing in an intact family at the age of 14, whereas 7.34% of individuals lived only with their mothers at that age. The majority (96.37%) have siblings. The cases of one, two, three and four siblings account for 25.63%, 30.71%, 18.20% and 9.94% of the total sample. About one-third of the individuals (34.32%) are the eldest child in the family. Table 3 also provides statistics on parental education and occupations when the individual was age 14. 57.98% of fathers and 37.78% of mothers have a college degree. Most fathers were employed, but only about half the sample had working mothers. Almost two-thirds of fathers' jobs were in white-collar occupations. Half of the working mothers worked in blue-collar jobs.

[4]A detailed comparison of the personality traits measurement between three waves will be provided in section 3.3.

[5]According to the report of Wooden (2013), the response rate is high, approximately 93%.

[6]All the parental questions are conditional on the situation when the respondent was at the age of 14.

[7]They are Australian Capital Territory(ACT), New South Wales(NSW), Victoria(VIC), Queensland(QLD), South Australia(SA), Western Australia(WA), Tasmania(TAS) and Northern Territory(NT).

3.2 Educational and occupational choices over life cycle

During the survey, individuals report both school enrollment and employment information annually. Details include the desired education level and whether they eventually reach this level.[8] The employment information includes employment status, working hours, total annual earnings and occupational codes.

Figure 1 shows the choice distribution of schooling, staying at home, blue collar jobs and white collar jobs by age. At age 15, about 80% are enrolled in school but after age 17, this fraction drops sharply to around 30%. The majority of secondary school graduates choose to work immediately rather than to continue their tertiary education. The enrollment rate keeps decreasing from 19% at age 23 to around 9% at age 34.

An individual is defined to be "working" if reported to be working positive hours and not enrolled in school. An individual is defined to be "staying home" if he is neither working nor in school.[9] The blue-collar participation rate decreases monotonically from around 50% at age 18 to around 38% at age 58. The significant increase of the white-collar participation rate between ages 22 to 25 suggests that a college degree is a prerequisite for many white-collar occupations. The white collar participation rate continues to increase after age 26, as some workers switch from blue-collar job to white-collar jobs over time. After age 53, the option of staying home becomes more prevalent, reflecting the retirement decisions of participants.

Figure 2 reports the age-earnings profile by two occupations, between ages 18 to 58.[10] Both the white-collar and blue-collar earning profiles exhibit a hump shape, overall. Prior to age 24, earnings of white-collar and blue-collar workers are similar. Subsequently, however, the shape of the blue-collar earnings profile becomes flatter and then stops growing after age 28. The white-collar earnings profile keeps increasing until the mid-30s. Peak average earnings from blue-collar jobs is around AU$48,000, whereas the peak from white-collar jobs is around AU$85,000. Earnings in both sectors decrease slightly at older ages.

Data on personality traits are gathered in 2005, 2009 and 2013. Table 4 reports the average personality trait scores for three different educational levels: senior secondary school or lower, college dropouts and college graduates. In general, the group with higher educational attainment has higher scores of emotional stability, openness to experience, conscientiousness, and agreeableness. However, this group tends to be less extraverted. Table 5 reports the difference between these workers in personality traits between workers in white-collar and blue-collar jobs. Workers in white-collar occupations are more likely to be emotionally stable, open to experience, and conscientious, but are less extraverted. The most significant differences come from conscientiousness and openness to experience.

[8] A rough classification of the tertiary education certificates includes 1. Certificates I-IV; 2. Diploma, Advanced Diploma, Associate Degree; 3. Bachelor degree and honors; 4. Graduate Certificate and Graduate Diploma; 5. Master degree; 6. Doctoral degree.

[9] We do not distinguish between being unemployed and being out of labor force, as the decision to be unemployed is always considered voluntary under our model.

[10] We drop the wage observations between age 15 and age 17 because of two reasons. 1. the observations are few. 2. A Large fraction of this group are senior school students who only do some part-time jobs. Thus their choices is classified as schooling according to our definition.

3.3 Stability of personality traits

The stability of personality traits is an important issue discussed both in the psychology and economics literature. Some studies find that personality traits are stable for adults (Terracciano et al. (2006), Terracciano et al. (2010)). Other studies find evidence of changing personality traits, particularly during younger ages (Almlund et al. (2011), Cunha and Heckman (2007), Cunha et al. (2010)). In this section, we use the HILDA data to examine the malleability of personality traits over the life cycle. We calculate average personality trait scores over the life cycle using the wave 13 sample (figure 3). After that, we investigate how working and schooling behaviors correlate with observed changes in personality (table 6), the main channel through which personality impacts agents in the structural model.

Figures 3(a) to 3(e) present the average score of "big-five" over the life cycle using the 2013 wave. Compared with the other three traits, openness to experience and emotional stability are relatively more persistent. Conscientiousness and agreeableness increase over time, with the greatest increase observed among respondents under the age of 35. Extraversion decreases with age until age 35, and then stays stable. Overall, traits appear to be more malleable for younger respondents.

We next investigate how education and working experiences correlate with personality change. To this end, we regress the changes of the Big-Five personality scores, standardized to mean 0 and variance 1, in the medium-run and in the long-run, defined as between years 2005-2008 and years 2005-2013, on years of experience in blue-collar and white-collar jobs and on years of schooling. The estimates are shown in table 6. Occupational experience shows little relationship with personality changes but education is related. During an eight-year time window, a male with one more year of schooling becomes more agreeable (0.032 std. dev.) and more conscientious (0.066 std dev.). The intercept term captures the age trend in personality traits and shows an increase in conscientiousness (0.105 std dev.) and emotional stability (0.090 std dev.) per one-year age growth.

3.4 Correlation between personality traits and schooling and occupational choices

We next estimate probit and linear regression models to investigate how personality traits correlate with individuals' college attendance and occupational choice decisions and wage performance. $D = 1$ if an individual has ever attended any form of college education by age 26, else $D = 0$. $D_0 = 0$ for individuals with blue-collar jobs and $D_0 = 1$ for individuals with white-collar jobs.

$$
\begin{aligned}
Pr(D=1) &= \Phi(X\beta_D + \lambda_D'\theta_n + \gamma_D'C + \epsilon_D) \\
Pr(D_o=1) &= \Phi(X\beta_{D_o} + \lambda_{D_o}'\theta_n + \gamma_{D_o}'C + \epsilon_{D_o}) \\
\log w_{00} &= X\beta_{00} + \lambda_{00}'\theta_n + \gamma_{00}'C + \epsilon_{00} \quad D=0 \ \& \ D_o=0 \\
\log w_{10} &= X\beta_{10} + \lambda_{10}'\theta_n + \gamma_{01}'C + \epsilon_{10} \quad D=1 \ \& \ D_o=0 \\
\log w_{01} &= X\beta_{01} + \lambda_{01}'\theta_n + \gamma_{10}'C + \epsilon_{01} \quad D=0 \ \& \ D_o=1 \\
\log w_{11} &= X\beta_{11} + \lambda_{11}'\theta_n + \gamma_{11}'C + \epsilon_{11} \quad D=1 \ \& \ D_o=1
\end{aligned}
$$

w_{D,D_o} represents the average earnings between ages 26-30 conditional on the schooling choice D and occupational choice D_o. The X variables include family background characteristics including an intact family dummy, parental occupations, parental education level, sibling number, sibling order, cohort effect and geographical locations. θ_n denotes the mean value of "Big-five" measurements in wave 5, 9 and 13.[11] C represents the value of cognitive ability.

Table 7 shows how personality traits and cognitive ability relate to college attendance decisions. Probit 1 only includes personality traits only whereas probit 2 includes additional controls for family background characteristics. The estimates indicate that the college attendance is mainly correlated with openness to experience, conscientiousness and extraversion. Although a unit standard deviation in extraversion decreases college attendance by 4.5%, the same increase in openness to experience and conscientiousness increases the probability of college enrollment by 6.6% and 4.3% percent. Because openness to experience represents an intrinsic interest in learning and conscientiousness demonstrates the desire to do task well, it is perhaps not surprising that both would be associated with higher college attendance. For comparison, a one standard deviation increase in cognitive ability increases the probability of entering college by 15.7%.

Table 8 shows the relationship between personality traits and occupational choices. The first regression only includes personality traits, whereas the second and the third regressions add family background characteristics and family background characteristics plus college choices. Conditioning on college attainment and family background, a one standard deviation increases in openness to experience increases the probability of having a while-collar job by 6.6%. At the same time, a one standard deviation increase in conscientiousness raises the probability of having a white-collar job by 2.4%.

Table 9 examines how personality traits relate to wages for four educational and occupational groups. Among all personality traits, conscientiousness and openness to experience are the dominant traits in pre-

[11] We normalized the score of each trait to be mean 0 and variance 1 before taking the average values across three data waves.

dicting wage differences. A one standard deviation increase in conscientiousness causes an earnings increase of about 10% for white-collar workers and about 7% for blue-collar workers. The other trait, openness to experience, surprisingly has negative effect on wage performance. These negative values are significant in blue-collar/no-college and white-collar/college groups.

4 The Model

We develop a discrete choice dynamic programming (DCDP) model of decision-making with regard to education, employment, and occupation sector over ages 15 to 58. At each age, individuals maximize their remaining discounted lifetime utility. The choice set in each year consists of four mutually exclusive options $m \in M$: working in either a blue- or white-collar occupation, attending school, or staying home. Let $d_m(a) = 1$ if the alternative m is chosen at age a, $d_m(a) = 0$ otherwise. Individual endowments at age 15 consist of personality traits, cognitive ability, and family background characteristics. These include parental schooling, the number of siblings, sibling order and whether the person lived with both parents at age 14. To allow for unobservable heterogeneity in a tractable way, we assume each individual is one of four types $k(a) = \{1, 2, 3, 4\}$. An individual's type can affect their pecuniary and nonpecuniary reward from choosing particular alternatives. One important innovation in our model that deviates from literature (e.g. Keane and Wolpin (1997)) is that it allows types to evolve over time in a way that may depend on age and changing personality traits.

We use $\Theta(a)$ to represent personality traits and $k(a)$ to denote the unobserved types at age a, which are assumed to be known by the individual but not known by econometricians. $s_o(a)$ represents all other observed state variables. At age 15, the initial type $k(15)$ is determined by the initial endowment $s_o(15)$. Then given the initial type $k(15)$ and observed state variables $s_o(15)$, the agent chooses the alternative $d_m(a)$ that gives the highest continuation value. The state variables, $s_o(16)$, are updated according to the choice $d_m(15)$, and then the new type $k(16)$ is drawn depending on $s_o(16)$ and the type of the previous period $k(15)$.

4.1 Laws of motion for $s_o(a)$ and $k(a)$

The time-varying part of $s_o(a)$ consists of four components so that $s_o(a) = (g(a), x_1(a), x_2(a), \Theta(a))$. $g(a)$ represents accumulated education while $x_1(a)$ and $x_2(a)$ represent accumulated blue-collar and white-collar experience at age a. We first specify the law of motion for states $g(a), x_1(a), x_2(a)$ and then discuss the transition probability functions governing the personality traits $\Theta(a)$ and types $k(a)$.

Years of schooling and occupation-specific experience evolve in a deterministic way. More specifically, the updating of $g(a), x_1(a)$ and $x_2(a)$ are defined as follows:

$$\begin{aligned} g(a) &: g(a+1) = g(a) + d_m(a) \\ x_i(a) &: x_i(a+1) = x_i(a) + d_m(a), i = \{1,2\} \end{aligned} \tag{1}$$

As shown in section 3.3, personality traits are correlated with education but not with work experience. We assume that the true $n-th$ personality trait $\theta_n \in \Theta, \{n = 1,2,3,4,5\}$ is measured with error, which the measurement error shock denoted $\zeta_n(a)$. We adopt the following specification for the evolution of each trait:

$$\begin{aligned} \theta_n^M(a+1) &= \theta_n(a+1) + \zeta_n(a+1) \\ \theta_n(a+1) &= \theta_n(a) + \gamma_{0n} + \gamma_{1n}(a-15) + \gamma_{2n}d_3(a) + \gamma_{3n}(a-15)d_3(a) \end{aligned} \tag{2}$$

where $\theta_n^M(a+1)$ is the measure of the nth personality trait at age $a+1$ and $\theta_n(a+1)$ is the true trait without measurement error. γ_{0n} and γ_{1n} capture the age effects. The term $\gamma_{2n} + \gamma_{3n}(a-15)$ captures a potential age*education interaction effect.

As previously described, we allow the unobserved types to change in a way that may depend on age and on personality characteristics. We specify a Markov process through which types evolve. After the initial period, the type $k(a)$ can stay the same with probability $1-p(a)$ or change to a new type with probability $p(a)$.[12] Conditional on a type changing, we use notation $q_k(a)$ to represent the probability of becoming type $k \in \{1,2,3,4\}$. Let $L(a)$ denote the Markov transition matrix of types between period a to period a+1. The matrix has the following form:

$$L(a) = p(a) \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} + (1-p(a)) \begin{bmatrix} q_{k=1}(a) & q_{k=1}(a) & q_{k=1}(a) & q_{k=1}(a) \\ q_{k=2}(a) & q_{k=2}(a) & q_{k=2}(a) & q_{k=2}(a) \\ q_{k=3}(a) & q_{k=3}(a) & q_{k=3}(a) & q_{k=3}(a) \\ q_{k=4}(a) & q_{k=4}(a) & q_{k=4}(a) & q_{k=4}(a) \end{bmatrix} \tag{3}$$

where

$$p(a) = \frac{1}{1 + \exp(\gamma_7 + \gamma_8(a-15) + \gamma_9(a-15)^2)} \tag{4}$$

$$q_k(a) = \frac{\bar{v_k^a}(\Theta, c)}{\Pi_{k=1}^{K=4} \bar{v_k^a}(\Theta, c)} \tag{5}$$

$$\log \bar{v_k^a}(\Theta, c) = \gamma_{3k} + \sum_{n=1}^{N=5} \gamma_{4kn}\theta_n(a) + \gamma_{5k}c + \sum_{z=1}^{Z} \gamma_{6zk}d_z + \eta_k(a) \tag{6}$$

[12]We assume the changing probability $p(a)$ does not vary by type k, so that different types have the same persistence at the same age.

At age 15, the initial types are directly drawn from the distribution $q_k(15)$. In subsequent ages, types are updated following the Markov transition matrix $L(a)$. When $p(a)$ is close to 0, then $L(a)$ corresponds to an identity matrix $I_{4\times4}$ and the types, k, are fixed. When $p(a) = 1$, types do not persist from previous period. We estimate $p(a)$, allowing for the possibility that types become more or less persistent with age. The probability of each type $q_k(a)$ follows a multinomial logit form (equation 5). Equation 6 captures the correlation between types and their determinants, including current personality traits $\theta_n(a)$, cognitive skill c as well as background characteristics $d_z(a)$.

4.2 Rewards associated with each alternative

An individual can choose to work in either a blue-collar occupation or a white-collar occupation. The reward to a particular sector include the wage compensation $w_m(a)$ and any non-pecuniary reward $r_m(a)$. $\epsilon_m(a)$ is the preference shock when choosing $m-th$ alternative. $m = 1$ denotes the blue-collar alternative and $m = 2$ the white-collar alternative. This yields the following utility function at age a:

$$u_m(a) = w_m(a) + r_m(a) + \epsilon_m(a), m = \{1, 2\} \tag{7}$$

As in Keane and Wolpin (1997), the wage is specified as a human capital pricing equation. It is given by the product of the price per unit of human capital p_m and the amount of human capital $e_m(a)$ embodied in the individual. That is $w_m(a) = p_m e_m(a)$. Human capital is accumulated through work experience and by attending school:

$$\begin{aligned} e_m(a) = exp(&e_m^k + \sum_{i=1}^{I} \beta_{m0i} d_i + \beta_{m1} g(a) + (\beta_{m2} + \beta_{m3} I\{x_m(a) \leq 2\}) x_m(a) \\ &+ \beta_{m4} x_m^2(a) + \beta_{m5} x_m(a) g(a) + \xi_m(a)) \end{aligned} \tag{8}$$

which yields a log-wage equation the form:

$$\begin{aligned} \log w_m(a) = \log p_m + e_m^k + &\sum_{i=1}^{I} \beta_{m0i} d_i + \beta_{m1} g(a) + (\beta_{m2} + \beta_{m3} I\{x_m(a) \leq 2\}) x_m(a) \\ &+ \beta_{m4} x_m^2(a) + \beta_{m5} x_m(a) g(a) + \xi_m(a) \end{aligned} \tag{9}$$

In (9), $d_i, i \in \{state \times cohort\}$ denotes a fixed effect of being a member of particular age cohort and residing in a particular state. e_m^k is the type-specific component of reward, which represents the advantage or disadvantage of type k when choosing alternative m. $g(a)$ represents the years of schooling and $x_m(a)$ denotes the working experience in sector m. The component $\beta_{m3} I\{x_m(a) \leq 2\} x_m(a)$ captures a potential differential in returns to experience when the agent is new in an occupation (has two years or less experience). The component $\beta_{m5}x_m(a)g(a)$ captures the interaction term between working experience $x_m(a)$ and education year $g(a)$, included to allow returns to experience to differ with education. $\xi_m(a)$ is a skill technology shock, which follows a i.i.d. normal distribution.

The second term in equation (7), $r_m(a)$, represents nonpecuniary aspects of choosing a certain occupation (such as working hours flexibility) expressed in monetary equivalent units. For the purpose of identification, we normalize the nonpecuniary utility from white-collar job $r_1(a)$ equal to 0. We allow the non-pecuniary utility from the blue-collar job $r_2(a)$ to vary with education level.

$$\begin{aligned} r_1(a) &= 0 \\ r_2(a) &= \beta_5 + \beta_6 I[g(a) \leq 12] \end{aligned} \tag{10}$$

If a person chooses to attend school, the per-period utility consists of two parts: a nonpecuniary component, which may reflect such as physical and mental costs when attending school, and a pecuniary component, such as tuition costs and fees. Thus, we have a school utility at age a defined by:

$$\begin{aligned} u_3(a) = e_3^k &+ \sum_{z=1}^{Z} \alpha_z d_z + \sum_{r=1}^{R} \alpha_r d_r + \alpha_0 I(age < 19) - \alpha_1 I(college) \\ &- \alpha_2 I(graduate) + \epsilon_3(a) \end{aligned} \tag{11}$$

The indicator d_z captures the potential effect of family background on a person's preference for attending school.[13] d_r is a cohort-specific effect. The term $\alpha_0 I(age < 19)$ captures the extra utility of attending school when the agent is under the age 19. α_3 and α_4 are per period schooling costs of attending college and attending graduate school. Lastly, e_3^k is the type-specific reward from attending school.

The reward from staying home, $u_4(a)$, consists of the type-specific component e_4^k, an age effect and an age squared effect, α_3 and α_4, and a home-staying preference shock $\epsilon_4(a)$, i.e.:

$$u_4(a) = e_4^k + \alpha_3 \cdot age + \alpha_4 \cdot age^2 + \epsilon_4(a) \tag{12}$$

It is worthwhile to mention that personality traits do not directly appear in the choice-specific utilities. Instead, they affect the choices indirectly through their influence on an individual's type probability. In addition, different types have different type-specific component e_m^k in each choice m. This structure reduces the dimensionality of the state space as it avoids the need to include a five-dimensional personality trait vector in the time-varying state space.

[13] The family background information includes sibling numbers, birth order and parental education level.

4.3 Information structure

In our model, individual heterogeneity comes from two sources: ex-ante endowments $s(15)$[14] and ex-post realized shocks $(\epsilon_m(a), \xi_m(a), \zeta_n(a), \eta_k(a))$. In terms of timing, we assume that the shocks governing the evolution of personality and of types are realized first, allowing individuals learn whether their type changed. After that, individuals observe preference shocks and choose their preferred sector. After this choice, wage shocks are realized.

Let $S^v(s) \subseteq S$ denote the set of visited states and $S^f(s) \subseteq S$ as the set of feasible states that can reached from s. Given the earlier time-line assumptions, we define $\iota(s)$ as the information set of the agent in state s by specifying all components known in the state, where

$$\iota(s) = \begin{cases} \epsilon_m(a); \zeta_n(a); \xi_m(a); \eta_k(a): & \text{for all } s(a) \in S^v(s) \\ \epsilon_m(a+1): & \text{for } s'(a+1) \in S^f(s) \\ k(15), \Theta(15), c, Z, state, cohort; \Omega: & \text{and for all s} \end{cases}$$

An individual in state s knows all state variable laws of motion, $\Pr(s(a+1)|s(a), d_m(a))$. He uses the distribution of wage shocks $F_m(\xi(s))$, idiosyncratic preference shocks $F_m(\epsilon(s))$, traits transition shocks $F_n(\zeta(s))$ and type transition shocks $F_k(\eta(s))$ to form an expectation over future states. For computational simplicity, $\xi_m(a)$ and $\zeta_n(a)$ are assumed to be uncorrelated and normally distributed, whereas $\epsilon_m(a)$ and $\eta_k(a)$ are assumed to be type I extreme value distributed. Conditional on the unobserved types, the other shocks are assumed to be iid over time.

5 Identification

The general procedure for incorporating multinomial types into longitudinal models dates back to Heckman (1981), Heckman and Singer (1984). The method was first used in the context of discrete choice dynamic programming (DCDP) models with fixed types in Keane and Wolpin (1997). The identification of serially correlated, unobserved types for a discrete choice model that satisfies a first-order Markov distribution is shown in Hu et al. (2015). Their identification strategy imposes one additional "limited feedback" restriction: namely that the type evolution is independent of choices m_{t-1} after conditioning on state variables s_{t-1}. This "limited feedback" assumption is satisfied in our model.[15] Following the argument in section 2.2 in Hu et al. (2015), one can nonparametrically identify both the distributions of unobserved types and the law of motions of all state variables (including unobserved types) using at least three time periods of data.

[14] the full list of state variable includes $s(a) = \{k(15), \Theta(15), c, Z, state, cohort\}$

[15] Hu et al. (2015) also requires the stationary assumption of the Markov kernel, which is a common assumption in I/O applications(i.e. dynamic games). Their conclusion can be generalized to our case where the conditional choice probability is age-dependent.

As the model is finite horizon, the case for identification of some of the model parameters can be made using the last time period. Wages in the blue collar and white collar sectors are observed. We impose a timing assumption on the model that individuals choose sectors after observing preference shocks but before observing wage shocks. Therefore, there is no selection problem in estimating the wage equation.

The utility values associated with the schooling choice and with the home choice as well as the nonpecuniary values of choosing a white or blue color job are not directly observed. In the last time period, the set-up of the choice problem is analogous that of a multinomial logit model given the types. Identification of these kinds of models is discussed in Horowitz (1981). The choices we observe allow us to infer relative but not absolute utilities, so identification requires normalizing one of the utility values. We normalize the nonpecuniary value of the white collar sector choice to be zero. Lastly, the difference in conditional choice probabilities by type identifies the type-specific components e_m^k of the flow utility functions.

Personality traits are observed in multiple time periods, so it is possible to directly estimate the transition process where personality traits at any time period are a function of lagged personality traits and of age following equation 2. The final parameter that we need to identify is the discount rate. The discount rate is identified through functional form assumptions that allow separation of the current period utility from future expected utility.

6 Estimation Strategy

6.1 Solving the dynamic programming problem

At the beginning of age a, an individual has the state vector $s(a)$, determined by his choices up to age a. As previously described, the evolving state variables include the accumulated sector-specific experience $x_i(a), i = 1, 2$, the completed schooling $g(a)$, personality traits $\Theta(a)$ and unobserved types $k(a)$. [16] Let $d_m(t) = 1$ denote that alternative m is chosen at age t. The value function at age a is the maximum over all possible sequences of future choices:

$$V(s(a), a, \Omega) = \max_{\{d_m(t)\}} E\left[\sum_{t=a}^{A} \delta^{\tau-a} \sum_{m=1}^{4} u_m(t) d_m(t) | s(a), \right]$$

where Ω denotes a set of parameter values. The summation over t denotes the ages and the summation over m denotes the different sector choices. The problem can be written in Bellman equation form.

[16] The personality traits at the initial age may not directly be observable, so in some cases we infer them using the approach described in Appendix A.

The alternative specific value function is

$$V_m(s(a),a,\Omega) = \tilde{u}_m(s(a),a) + \delta E\left[V(s(a+1),a+1,\Omega)|s(a),d_m(a)\right]$$

for $a < A$, and

$$V_m(s(A),A,\Omega) = \tilde{u}_m(S(A),A)$$

in the last time period. As previously noted, to facilitate computation, we impose an assumption on the timing of the model that the sector is chosen after preference shocks are realized but before the wage shock is realized. We denote $\tilde{u}_m(s(a),a)$ to be $u_m(s(a),a)$ after integrating over the wage shock distribution (i.e. $\tilde{u}_m(s(a),a) = \int_{\xi_m(a)} u_m(s(a),a)f(w(\xi_m(a)))d\xi_m(a))$. Wages in the white and blue collar sectors are assumed to be both normally distributed and uncorrelated. The expectation in the Bellman equation is taken over future wage and preference shocks and over the random process that governs the transition of personality traits and the unobserved types. [17]

The value function is the max over the alternative specific value functions:

$$V(s(a),a,\Omega) = \max_{m\in M} V_m(s(a),a,\Omega)$$

Recall that the preference shocks enter additively into $u_m(s(a),a)$ and, for computational simplicity, are assumed to follow an i.i.d. type I extreme value distribution with a location parameter 0 and a common scale σ_c.

Let $\tilde{V}_m(s(a),a,\Omega)$ denote the choice-specific value function excluding the contemporaneous sector-specific preference shock $\epsilon_m(a)$,.

$$V_m(s(a),a,\Omega) = \tilde{V}_m(s(a),a,\Omega) + \epsilon_m(a).$$

Because of the distributional assumption on the preference shocks, we have

$$\Pr(d_m(a)=1|s(a),\Omega) = \frac{\exp(\tilde{V}_m(s(a),a,\Omega)/\sigma_c)}{\sum_{j=1}^{4}\exp(\tilde{V}_j(s(a),a)/\sigma_c)}$$

As shown by Rust (1987), the expected value function can be written as

$$\begin{aligned} E\left[V(s(a+1),a+1,\Omega)|s(a),d_m(a)\right] &= E_{\epsilon_m(a)} \max_{d_m(a)} \textstyle\sum_{m=1}^{4} d_m(a)\{\tilde{V}_m(s(a),a,\Omega)+\epsilon_m(a)\} \\ &= \sigma_c \log\left(\textstyle\sum_{m=1}^{4} exp(\tilde{V}_m(s(a),a,\Omega)/\sigma_c)\right) + \sigma_c\gamma \end{aligned}$$

[17] Even though the realized wage shocks do not affect the contemporaneous utility associated with different sectors, the expected value functions will depend on the variance of the wage shocks.

where γ is the Euler's constant and σ_c is the scale parameter of the preference shock.[18]

The dynamic programming problem is solved using backward recursion for each set of parameter values under consideration. That is, in the last period A, when there is no future expected value function and using the previous equation, one obtains $E\left[V(s(A),A)|s(A-1),d_m(A-1),A-1\right]$ for each possible point in the state space. Plugging in $E\left[V(s(A),A)|s(A-1),d_m(A-1),A-1\right]$ into $\tilde{V}_j(s(A-1),A-1)$, one can then use the same expression to obtain $E\left[V(s(A-1),A-1)|s(A-2),d_m(A-2),(A-2)\right]$ and so on, back until the first time period.

After solving the dynamic programming problem, one obtains the expected future value functions for all possible state points. It is then possible to use the model to simulate choices and to implement a simulated method of moments optimization algorithm to estimate the parameters.

6.2 Simulated Method of Moments estimation

Our model parameters are estimated by simulated method of moments. We use an unconditional simulation approach starting from age 15, because occupation-specific experience stocks are not observed at the time of sampling. The simulation process is briefly summarized as follows:
For each individual i, given a set of trial parameters Ω:

1. Solve backward for choice-specific value function $V_m(s(a),\Omega)$ and choice probability $\Pr(d_m(a)|s(a),\Omega)$ following the procedure described in the previous section.

2. Impute initial personality traits $\theta_n(15)$ following the procedure described Appendix A. Initial unobserved types $k(15)$ are drawn from equation 5.

3. Starting from $s(15)=g(15)=0, x_i(15)=0, k(15), \theta_n(15)$, we simulate sequential shocks $\{\epsilon_m(a),\zeta_n(a),\xi_m(a),\eta_k(a)\}$ and compute the following outcomes: (1) agents' lifetime choices $d_m(a)$; (2) wage realizations $w_m(a)$ when $m=\{1,2\}$, $a=\{18,...,58\}$; and (3) personality traits $\theta_n(a), n=\{1,2,...,5\}$.

The simulation process is repeated for all i=1,2,...,N individuals, given their initial state variables. We then compute R moments using both the N simulated samples and the observed data, and then calculate the weighted difference between those R simulated moments $\tilde{M}_{N,R}(\Omega)$ and the data moments M_R, using the following objective criterion:

$$\hat{\Omega}_{N,R,W}=\arg\min_{\Omega}\left((M_R-\tilde{M}_{N,R}(\Omega))'W_R(M_R-\tilde{M}_{N,R}(\Omega))\right) \tag{13}$$

[18]This closed form representation of the value function is a big advantage in estimation because, without it, numerical integration over the structural errors is required to get the expected value function. It also generates an analytic one-to-one mapping between the choice probability and utility level of each choice. This tractable i.i.d. generalized extreme value (GEV) distributions assumption is also adopted in other recent DCDP papers such as Chan (2013) and Kennan and Walker (2011).

where M_R denotes the data moments, and $\tilde{M}_{N,R}(\Omega)$ represents the simulated moment evaluated at the parameter set Ω based on N repeated simulations.[19]

We use the variance information of each data moment to form the weighting matrix, W_R. Del Boca et al. (2014) show the consistency for this type of estimator for large sample sizes, $plim_{N\to\infty}\tilde{M}_{N,R}(\Omega_0) = M_R(\Omega_0)$.[20] In total, we match 505 moments to estimate 124 parameters. The following types of moments are used in our estimation:

1. Sequential life-time choices:
    - The fraction of individuals in the blue-collar occupation sector by age (15-58).
    - The fraction of individuals in the white-collar occupation sector by age (15-58).
    - The fraction of individuals in school by age (15-58).
    - The fraction of individuals at home by age (15-58).
2. Earning profiles[21]
    - Average log earnings of blue-collar workers by age (18-58).
    - Average log earnings of white-collar workers by age (18-58).
    - The standard error of log earnings of blue-collar jobs by age (18-58).
    - The standard error of log earnings of white-collar jobs by age (18-58).
3. Personality traits
    - Mean value of openness to experience by four-year age groups and by waves.[22]
    - Mean value of conscientiousness by four-year age groups and by waves.
    - Mean value of extraversion by four-year age groups and by waves.
    - Mean value of agreeableness by four-year age groups and by waves.
    - Mean value of emotional stability by four-year age groups and by waves.

[19]This unconditional simulation algorithm is often used to estimate dynamic discrete choice models when some state variables are unobserved(e.g. Keane and Wolpin (2001), Keane and Sauer (2010)). The consistency and other asymptotic properties of this estimator based on unconditional simulation are discussed in Gourieroux and Monfort (1996), section 2.2.2.

[20]Compared with directly calculating the optimal weighting matrix, this method simplifies computation significantly. Altonji and Segal (1996) discusses that gains from using an optimal weighting matrix may be limited.

[21]We don't fit the earning between age 15-17 because too fewer observations have earning information at these ages.

[22]The four-year age groups are 15-18, 19-22, 23-26, 27-30, 31-34, 35-38, 39-42, 43-46, 47-50, 51-54, 55-58. The waves are 2005, 2009 and 2013.

7 Estimates

7.1 Parameter Values

Tables 10-12 show the model parameter estimates along with standard errors. Table 10 shows the parameters corresponding to the per-period reward for each of the alternatives (white-collar job, blue-collar job, schooling, and home staying). An additional year of schooling increases white-collar and blue-collar wage offers by 4.47 and 3.99 percent. The reward for the first two years' work experience ($exp \leq 2$) is relatively high. One year of white-collar experience increases white collar wage offers by 16.24 percent, and one-year of blue-collar experience increases blue-collar wages by 29.32 percent. Although white-collar experience does not have a significant return in blue-collar jobs, blue-collar job experience is rewarded in the white-collar sector. The non-pecuniary terms capture the psychic difference between working in a white-collar or a blue-collar job. As previously described, we normalize the non-pecuniary utility from a white-collar job to 0. The non-pecuniary blue collar job premium is AU$23,388 for individuals who are not college graduates but only AU$3,377 for college graduates.

For the schooling option, we estimate a utility of AU$15,554 per year if an individual stays in school until age 17; a relatively high utility is needed to capture the drop-off in schooling after high school graduation. We find a net lump-sum cost of college education of AU$135,199 and a one-time cost of graduate school of AU$108,251.[23] This cost includes both tuition and living expenditures as well as potential psychological costs.

With regard to the option of home staying, the flow utility is specified as quadratic in age. The utility of staying home increases from AU$13.8 at age 15 to AU$7,635 at age 58. Lastly, we estimate a discount rate parameter, β, equal to 0.8960 and preference scale parameter σ_c equal to 0.9195.

There is considerable variation in the estimated rewards across occupations for the unobserved types. For the two working options, types I and II have comparative advantages. Type I receives the highest reward in the white-collar occupation and type II receives the highest reward in the blue-collar occupation. With regard to the schooling alternative, type I gets the highest reward from attending school, followed by types IV, II and III. The benefit of type I is only slightly higher than that of type IV (AU$8,058), but much higher than for types II (AU$37,180) and III (AU$76,862). For the option of staying home, the rewards of type I-IV are AU$44,872, AU$34,853, AU$21,972 and AU$33,538.

Table 11 shows how estimated type probabilities relate to cognitive ability, personality traits and family

[23]We compare our estimated costs with the real cost collected in Australia. For example, a 2014 HSBS report lists a per year cost for undergraduate study as AU$42,093, which includes AU$24,081 for fees and AU$18,012 for living costs. Source: http://www.about.hsbc.com.au/news-and-media/australia-the-most-expensive-country-for-education-hsbc-report. Another official website for Australia gives annual tuition fees for Bachelor's degree, Master's degree, and Doctoral degree in the range of AU$15,000-AU$33,000, AU$20,000-AU$37,000 and AU$14,000 to AU$37,000, respectively. Source: http://www.studyinaustralia.gov.au/global/australian-education/education-costs/education-costs-in-australia

background. Both personality traits and cognitive ability are important in type determination. High cognitive ability leads to a high probability of being type I and a relatively low probability of being type III or type IV. A high score of openness to experience implies a high probability of being types I or IV but a low probability of being type II. A person with high conscientiousness is more likely to be type I but less likely to be types II or IV. High agreeableness leads individuals to be type II rather than type I. The last two rows of table 11 show the malleability of types over time and how types become more persistent with age. As shown in figure 4, the probability of changing type starts at around 0.4 at age 15 then diminishes to 0 around age 34. In other words, our estimation results show that the types become relatively fixed in the mid-30s.

Table 12 shows the estimates of the probability that personality traits change, which is assumed to potentially depend on education and age.[24] Education has positive and significant effects only for the conscientiousness and agreeableness traits. One additional year of education at age 15 increases the level of conscientiousness and agreeableness by 4.60% and 3.64%, whereas it increases openness to experience, extraversion and emotional stability by only 0.22%, 0.49% and 0.79%.[25] The negative estimated coefficient on the interaction term between education and age (γ_{3n}) implies that the effect of education diminishes with age. For example, the effect of education on conscientiousness is negligible by age 55. The age effects on conscientiousness, extraversion and emotional stability are significantly larger than those on the other two traits. Conscientiousness increases with age at a diminishing rate. On the other hand, aging has an increasingly positive effect on emotional stability. Lastly, the results show that extraversion decreases with age.

7.2 Model Fit

Figures 5 and 6 display the data moments and compare model simulations with the data. The estimated moments pertain to three categories: the proportion choosing different sectors over life cycle (figure 5); the log wage of both white-collar and blue-collar occupations over life-cycle (figure 5); and the personality trait values over life-cycle (figure 6).

As seen in figure 5, the model captures salient features of data: (1) The fraction of blue-collar occupational choices exhibits an upward jump at age 18 and then declines gradually. (2) The fraction of white-collar occupation choices grows smoothly from nearly 0 at age 18, reaches its peak in the mid-30s, and then moves downwards slowly. (3) Except for a small hump shape in the early 20s, the fraction that stays home

[24]Recall that personality trait changes were found to be strongly associated with schooling and to change with age up until the mid 30s, but were not found to be associated with white collar or blue collar job experience.

[25]By comparison, Schurer et al. (2015) find that university education increases scores on agreeableness for male students from low socioeconomic backgrounds but has no effect on conscientiousness. Our sample includes individuals with both senior secondary and university education, whereas their sample focuses only on individuals with university education. Li and Powdthavee (2014) studies the effect of a policy change that increased the compulsory minimum leaving school age, using HILDA data, and concludes that the average conscientiousness rises after the reform.

exhibits a slow but persistent increase over the life cycle. (4) The fraction in school rapidly drops at age 18. Subsequently, a moderate decreasing trend takes over until it eventually reaches a stable level before age 39. (5) The concavity and the level of the earning profile are also captured by our simulated sample, both for white-collar occupation and blue-collar occupation. (6) Although the standard errors of log earnings from the data are more volatile, the simulated standard errors fit the observed average level reasonably well.

Figure 6 compares simulated personality traits and with the data measurements. In general, our simulated moments fit the data very well. Only 3 out of 165 moments fall outside of the 95% confidence interval generated by the corresponding data moments. Our simulations capture the following trait-specific patterns: 1. Openness to experience is quite stable over life-cycle. 2. Conscientiousness and emotional stability increase monotonically with age. 3. Extraversion decreases over time. 4. Agreeableness displays a hump shape during younger ages and then achieves a stable level after that.

8 Model Simulation Results

We next use the estimated model to simulate individuals' choices. First, we explore the link between personality traits, types and choices. Second, we examine the relative importance of personality traits in explaining the ex-ante heterogeneity compared with other initial endowments (e.g. cognitive ability, family background). Third, we implement a likelihood ratio test to test the hypothesis that the unobserved types are stable over time, which is assumed in many other studies. We reject this hypothesis.

8.1 Understanding the link between personality traits, types and choices

In this section, we examine the link between personality traits, types and lifetime choices. First, table 13 examines the type distributions within the different alternatives. The row labeled "original" shows the proportions of the four types within each alternative. The row labeled "adjusted" gives the fractions of each choices adjusted by the fraction of each type in the population. Our simulation results show that type I has a comparative advantage in schooling and in the white-collar sector. Type II has a comparative advantage in the blue-collar sector. Type III is more likely to be in the blue-collar sector or to stay at home. Type IV is more often at school or at home.

Table 14 shows mean personality trait values for all four types. The analysis reported in table 7 shows that the openness to experience trait has the biggest predictive power on education choices. Thus, the high scores of openness to experience of types I and types IV likely explain why these types have comparative advantages in schooling. Meanwhile, type II and type III's comparative advantages in the blue-collar sector stems from low levels of openness to experience and moderate levels of conscientiousness. Lastly, the over-representation of type IV in the home-staying sector is attributable to low scores on both emotional stability and conscientiousness.

Figure 7, a radar chart, compares average levels of personality traits and cognition among types. Each equi-angular spokes ("radii") represents one dimension of personality traits. Each star-like hectagon denotes the values of the "Big-five" along with the cognitive score for each type. It is clear that type I has the highest values of all five traits and for cognition, because its hectagon totally covers the other three types' hectagon. It seems that high cognitive ability and high values of personality traits tend to be clustered in type I individuals, who are those that tend to acquire more schooling and to work in the white collar sector.

Figure 8 shows how the fraction of types change for different age cohorts. With age, the proportions of type II and IV decrease while the proportions of type I and III increase. Those changes are driven primarily by increasing levels of conscientiousness. Our estimates in table 12 indicate that the average level of conscientiousness increases over time, both because of the accumulation of education and because of a direct effect of age. A higher conscientiousness score increases the probability of being type I or type III. Figure 4 plots the probability that types change over time. In general, types become more stable with age. The probability of switching types starts at around 0.4 at age 15 and diminishes to 0 by age 36.

8.2 Exploring the importance of personality traits in explaining ex-ante lifetime utility heterogeneity

To understand the importance of personality traits in explaining ex-ante utility heterogeneity, we estimate a linear regression where the dependent variable is the expected present value of lifetime utility at the age of 15 and the independent variables are personality traits at age 15, cognitive ability and family background. Table 15 summarizes the regression results under three different specifications of regressors: (i) only family background (ii) both family background and cognitive ability, (iii) personality traits, cognitive ability and family characteristics. The first two regressions are very comparable to model specifications reported in Keane and Wolpin (1997). They estimate a similar regression and report that adding Armed Forces Qualification test score(AFQT), the "ability" score measure, increases the R^2 from 0.10 to 0.14. In our case, including the cognitive ability measurement increase the R^2 from 0.095 to 0.121. When we estimate regression specification (iii) including, in addition, personality traits, we get a further increase in R^2 to 0.154.

8.3 Testing the hypothesis of type stability

A novel feature of our model relative to the literature is that unobserved types evolve over time and that the change is related to age and the evolution of personality traits. In this section, we test the validity of this assumption by comparing our model with an alternative "fixed types" model. In the fixed type model, the probability of each type does not depend on personality traits but is still determined by other age 15 endowments (e.g. family background). Types are assumed to be fixed after age 15. This assumption is almost the same as that of Keane and Wolpin (1997)[26].

Table 16 shows the null hypotheses of the alternative model specifications and its corresponding criteria function. The LR-test indicates that the "fixed type" model is rejected with a p-value less than 0.01.

9 Two education policy experiments: compulsory senior secondary school and a college subsidy

We next use the estimated dynamic discrete choice model, both the variable types and fixed types versions, to evaluate the effects of two education policies in Australia, a tuition subsidy program and a compulsory schooling policy.

9.1 Policy Background

Since the late 1980s, the Australian government started providing financial assistance to students through a program called the Higher Education Contribution Scheme (HECS) and, after 2005, the Higher Education Loan Programme (HELP). With the goal of relieving the financial burden of a university education, those eligible for HECS-HELP can either receive no interest student loans or get a 10 % discount on upfront payment. Some students also receive direct financial help to cover living expenditures through some means-tested programs (such as Austudy or Youth Allowance). Motivated by these financial aid programs, we use the model to simulate the effects of a hypothetical college cost abatement policy that reduces the cost of attending college by 50%.

Our second policy experiment is motivated by the spacial variation in the compulsory schooling years across different states and territories. The compulsory education policy in Australia is age-based. In 2009, the minimum school leaving age in Queensland, Western Australia, South Australia and Tasmania was 17, whereas the leaving age in other areas was between 15-16. [27] In 2010, areas with lower compulsory school attendance ages came up with plans to increase compulsory schooling.[28] As a result, the students in all states and territories now are required to stay in school until age of 17. (National Report on Schooling in Australia 2011) Inspired by these policies, we consider the imposition of a national compulsory secondary school education rule that forces all agents to stay in school until at least of age 17.[29]

[26]In Keane and Wolpin (1997), they assume the initial type distribution only depends on with initial schooling years(10 years or more V.S. nine years or less.) Then they calculate the conditional probability of becoming each type on individual's family background information. We model the dependence between the initial types distribution and family background characteristic directly

[27]Source: National Report on Schooling in Australia 2009.

[28]From 2010, New South Wales, Victoria, Northern Territory and Australian Capital Territory all claim that local students need to complete Year 10 and then participate in education, training or employment until they turn 17.

[29]We aware that the individuals who are younger than age 18 after the year 2009 in HILDA data should be already eligible

9.2 Estimated effects of two education policies

We next use model simulation to evaluate the previously described education policies. When evaluating the policy effects, we focus our attention on both their means and distributional effects. To understand the importance of allowing for time-varying types, we compare the simulated policy effects of 4215 individuals obtained under the baseline model to that obtained under the restricted "fixed type" model. The outcomes we compare include (1) educational attainment, for both senior secondary school and college graduates; (2) expected present value of lifetime utility gain at age 15.

Table 17 shows the effect of the two policies.[30] The upper panel considers the following five quantitative effects: (1)the percentage of high school graduates; (2) the percentage of college graduates; (3) the average years of education; (4) the annual earnings for working people; and (5) the expected lifetime utility gain. In each of these five categories, we first present the values under baseline model in the row labeled as "benchmark". The two rows labeled "50% college subsidy" and "compulsory senior secondary school" show the deviations from baseline values under two separated policy experiments.

Comparing the effects of two policies, two features stand out. First, the compulsory schooling policy has the most direct positive effect on the secondary school completion rate (+11.8%), whereas the college subsidy has the largest positive impact on the fraction of college graduates (+25.2%). However, because individuals are forward looking and graduation from senior secondary school is the prerequisite to attending college, the compulsory school policy also stimulates college graduation (+1.7%) and college subsidy policy also encourages senior secondary school completion (+0.2%). Second, these two policies affect different types of individuals. The college subsidy increases the average years of completed education by around one year for types I and IV but only by around a half year for types II and III. In contrast, the compulsory school policy increases years of education by about one half year for types II and III but has almost no effect for types I and IV.

We observe a similar pattern for labor market outcomes. Under the college subsidy intervention, types I and IV experience an average increase in annual earnings of AU$ 6,772.8 and AU$ 8,208.7. The increases observed for types II and III are only AU$ 2,389.8 and AU$ 2,340.0. When implementing the compulsory schooling policy, types II and III benefit the most. The annual earnings increases of those two types are AU$ 3,616.2 and AU$ 2,804.3, whereas the increases of other two types are only AU$ 606.2 and AU$ 451.0. The differences between types are caused by the original education level of each type. Secondary school completion is already so prevalent among types I and IV, thus few individuals of those types are affected

to the compulsory education policy. However, the policy enforcement, according to our calculation, is very limited. The school enrollment rates for the teenagers between 15-18 are 84.9%(175/206) in year 2010, 90.0%(226/251) in the year 2011, 89.8%(211/235) in the year 2012 and 83%(176/212) in the year 2013. These enrollment rates are stable and do not significantly different from years before 2009. Thus we assume no impact of any compulsory policy in our baseline model estimation.

[30] Because the types change over time and are potentially influenced by education, we classified agents according to their initial type at age 15.

by the compulsory schooling policy. These individuals are more likely to face the trade-off between finishing college or not and are most strongly influenced by the college subsidy policy.

The lower panel reports the effects of two policies on personality traits at age 30, when most of the population have completed their education. Under the category of each personality trait in table 17, the row "benchmark" demonstrates the average trait score of each type. The rows "50% college subsidy" and "compulsory senior secondary school" report the additional change of the "Big-Five" traits under these two policies. In general, the effects of both policies on traits are positive. However, the change of conscientiousness and openness to experience are one-order magnitude larger than the change of the other three traits. Conscientiousness increases by 0.026, equivalent to 0.93 of its standard error, under a 50% college subsidy policy and 0.015 (equivalent to 0.53 of its standard error) under compulsory senior secondary school policy. Meanwhile, openness to experience increases by 0.020, equivalent to 0.71 standard error, under a 50% college subsidy policy and 0.011 (equivalent to 0.39 standard error) under compulsory senior secondary school policy.

9.3 Understanding the importance of changeable types

To understand the empirical importance of allowing for changing types, we re-evaluate the effect of the same two policies under the restricted "fixed types" model. The results are reported in table 18. Compared with table 17, there are two main differences. First, the policy impacts are now more concentrated among types. The college subsidy policy only affects the college graduation decision of type I and type IV, while compulsory senior secondary school policy essentially only affects the senior secondary school certificate completion rate of type II and type III. Second, the effects on labor market outcomes are smaller. In our baseline model, the 50% college subsidy policy and the compulsory senior secondary school policy boost employed workers' average annual earnings by AU$ 4,718.7 and AU$ 2,210.4. In contrast, the earning increase drops to AU$ 2,943.7 and AU$ 1,592.8 in the restricted "fixed type" model.

The reason for these differences is fairly straightforward. When type is changeable, the education investment has both a direct reward for working and an indirect reward through the chance to become a different type. Table 19 shows the type distribution in each age group under the baseline model and under the two policies. When years of education increases, a larger fraction of type II and type IV agents switch to type I. [31] The "fixed types" model shuts down the second indirect channel. As a consequence, the marginal benefits of education is lower. Thus, the agents' educational incentives are underestimated accordingly, especially for the disadvantaged groups, which causes in an overestimation of the inequality of the policy effects.

[31] Although the proportion of type III also increases, the increment of type I is much larger.

9.4 Heterogeneous policy effects by family background social-economic status (SES)

Lundberg (2013) emphasizes the importance of family background in understanding the correlation between personality traits and college graduation. Therefore, we investigate the heterogeneous effects of two policies on individuals from different family backgrounds. The social-economic status is defined in terms of parents' educational attainment. In group I, both parents have education equal to high school or less. In group II, one parent has some college, and in group III, both parents have above high school graduation.[32] We find the personality patterns between individuals from different SES are exactly the same as those reported in Lundberg (2013). Individuals from more advantaged family backgrounds tend to have high scores for conscientiousness, openness to experience as well as emotional stability (the opposite of neuroticism).

Table 20 summarizes the effects of both the college subsidy policy and the compulsory senior secondary school policy. The policy effect of the college subsidy is almost equally distributed across the different SES groups in the term of education increase. The increases in conscientiousness are 0.025, 0.028 and 0.025 for Group I, II and III. [33] However, with regard to annual earnings increase, the benefits of the college subsidy policy accrue to more advantaged families. The earnings increase for Group I is AU$4410.2, while the earnings increase for Group III is AU$4869.6. On the other hand, the compulsory senior secondary school policy has larger effects on individuals from more disadvantaged backgrounds. The average education enhancement for Group I is 0.32 year, whereas the average increase of Group III is only 0.21 year. Considering the labor market outcomes, the earnings increase of Group I is AU$ 2,148.4, and the earning increase of Group III is AU$ 2,000.8. Regarding the personality traits, we observe a larger improvement for the least advantaged group in both conscientiousness (0.017 of Group I vs. 0.011 of Group III) and openness to experience (0.013 of Group I vs. 0.009 of Group III).

10 Conclusions

This paper develops a dynamic discrete choice model of schooling and occupational choices that incorporates time-varying "Big-Five" personality traits. As is common in the discrete choice literature, we introduce unobservable types' to capture agents' heterogeneous comparative advantages in schooling and in particular occupational sectors. One innovative feature of our model, however, is that we allow the unobserved types to change over time in a way that may depend on age and evolving personality traits. We find that personality traits are the most important factor in explaining the ex-ante heterogeneity, defined as "types" at age 15 in our model. We perform a likelihood ratio test to examine the assumption that types are fixed, which we

[32]We did not consider the family intactness as additional dimension, because the majority (82.89%) grew up with both biological parents in our sample.

[33]This increase is equal to about one standard error of the mean value.

strongly reject. Our estimation also shows that the types are more malleable when agents are young but become stable after age 36. Another interesting finding is that high levels of cognitive skills and high levels of personality traits, in all five dimensions, tend to be clustered in a certain type of individual. This is also the type that acquires more schooling and tends to work in white collar sector jobs. Much of the prior literature in economics emphasizes the role of cognitive skills, as measured by instruments such as the AFQT, but our analysis shows that high cognitive skills, on average, go hand-in-hand with high noncognitive skills, as measured by the Big Five Traits.[34] Our results suggest that the relevance of the cognitive dimension as a determinant of labor market success may be overemphasized in studies that ignore non-cognitive attributes, which are usually not considered because of data limitations.

Using the estimated dynamic discrete choice model, we evaluate two education policies: a compulsory senior secondary school policy and a 50% college subsidy policy. Both policies increase educational attainment, but their distributional effects are very different. The compulsory school policy is effective for groups who come from more disadvantaged backgrounds, whereas the college subsidy mainly benefits those who come from more advantaged backgrounds and already had a comparative advantage in the schooling sector. We show that a model with fixed types ignores the indirect reward of education in shaping personality, which is empirically important to consider when evaluating the distributional effect of these two policies.

Our results highlight the importance of personality traits in explaining ex-ante heterogeneity at age of 15, which, as was demonstrated in Keane and Wolpin (1997), is a major determine of ex-ante life-time inequality. We find that one of the benefits of attending school is that it changes personality characteristics, which, along with increased schooling levels, enhances earnings. One caveat to our findings is that personality endowments are measured as of age 15. They likely reflect parental investment and life experience from conception to age 15. As emphasized in Cunha et al. (2010), the most cost effective policies for fostering the accumulation of non-cognitive skills such as personality traits may be policies that are targeted towards individuals during early childhood years rather than high school or post-secondary schooling interventions.

[34] See, for example, Neal and Johnson (1996).

References

Almlund, M., Duckworth, A. L., Heckman, J. J., and Kautz, T. D. (2011). Personality psychology and economics. Technical report, National Bureau of Economic Research.

Altonji, J. G. and Segal, L. M. (1996). Small-sample bias in gmm estimation of covariance structures. *Journal of Business & Economic Statistics*, 14(3):353–366.

Becker, G. S. (1964). *Human Capital: A Theoretical and Empirical Analysis, with Special Reference to Education, by Gary S. Becker,...* London.

Borghans, L., Duckworth, A. L., Heckman, J. J., and Ter Weel, B. (2008). The economics and psychology of personality traits. *Journal of human Resources*, 43(4):972–1059.

Chan, M. K. (2013). A dynamic model of welfare reform. *Econometrica*, 81(3):941–1001.

Cubel, M., Nuevo-Chiquero, A., Sanchez-Pages, S., and Vidal-Fernandez, M. (2016). Do personality traits affect productivity? evidence from the laboratory. *The Economic Journal*, 126(592):654–681.

Cunha, F. and Heckman, J. (2007). The technology of skill formation. *American Economic Review*, 97(2):31–47.

Cunha, F. and Heckman, J. J. (2008). Formulating, identifying and estimating the technology of cognitive and noncognitive skill formation. *Journal of human resources*, 43(4):738–782.

Cunha, F., Heckman, J. J., and Schennach, S. M. (2010). Estimating the technology of cognitive and noncognitive skill formation. *Econometrica*, 78(3):883–931.

Dahmann, S. and Anger, S. (2014). The impact of education on personality: Evidence from a german high school reform.

Del Boca, D., Flinn, C., and Wiswall, M. (2014). Household choices and child development. *The Review of Economic Studies*, 81(1):137–185.

Fletcher, J. M. (2013). The effects of personality traits on adult labor market outcomes: Evidence from siblings. *Journal of Economic Behavior & Organization*, 89:122–135.

Goldberg, L. R. (1992). The development of markers for the big-five factor structure. *Psychological assessment*, 4(1):26.

Gosling, S. D., Rentfrow, P. J., and Swann, W. B. (2003). A very brief measure of the big-five personality domains. *Journal of Research in personality*, 37(6):504–528.

Gourieroux, C. and Monfort, A. (1996). *Simulation-based econometric methods*. Oxford university press.

Griliches, Z. (1977). Estimating the returns to schooling: Some econometric problems. *Econometrica: Journal of the Econometric Society*, pages 1–22.

Heckman, J. and Singer, B. (1984). A method for minimizing the impact of distributional assumptions in econometric models for duration data. *Econometrica: Journal of the Econometric Society*, pages 271–320.

Heckman, J. J. (1981). The incidental parameters problem and the problem of initial conditions in estimating a discrete time-discrete data stochastic process.

Heckman, J. J., Moon, S. H., Pinto, R., Savelyev, P. A., and Yavitz, A. (2010). The rate of return to the highscope perry preschool program. *Journal of public Economics*, 94(1):114–128.

Heckman, J. J. and Raut, L. K. (2016). Intergenerational long-term effects of preschool-structural estimates from a discrete dynamic programming model. *Journal of econometrics*, 191(1):164–175.

Heckman, J. J., Stixrud, J., and Urzua, S. (2006). The effects of cognitive and noncognitive abilities on labor market outcomes and social behavior. *Journal of Labor Economics*, 24(3):411–482.

Horowitz, J. (1981). Identification and diagnosis of specification errors in the multinomial logit model. *Transportation Research Part B: Methodological*, 15(5):345–360.

Hu, Y., Shum, M., Tan, W., and Xiao, R. (2015). A simple estimator for dynamic models with serially correlated unobservables. *Journal of Econometric Methods*.

Huggett, M., Ventura, G., and Yaron, A. (2011). Sources of lifetime inequality. *The American Economic Review*, pages 2923–2954.

Keane, M. P. and Sauer, R. M. (2010). A computationally practical simulation estimation algorithm for dynamic panel data models with unobserved endogenous state variables. *International Economic Review*, 51(4):925–958.

Keane, M. P. and Wolpin, K. I. (1997). The career decisions of young men. *Journal of political Economy*, 105(3):473–522.

Keane, M. P. and Wolpin, K. I. (2001). The effect of parental transfers and borrowing constraints on educational attainment. *International Economic Review*, 42(4):1051–1103.

Kennan, J. and Walker, J. R. (2011). The effect of expected income on individual migration decisions. *Econometrica*, 79(1):211–251.

Li, J. and Powdthavee, N. (2014). Does increasing schooling improve later health habits? evidence from the school reforms in australia. Technical report, Melbourne Institute of Applied Economic and Social Research, The University of Melbourne.

Losoncz, I. (2009). Personality traits in hilda1. *Australian Social Policy No. 8*, page 169.

Lundberg, S. (2013). The college type: Personality and educational inequality. *Journal of Labor Economics*, 31(3):421–441.

Neal, D. A. and Johnson, W. R. (1996). The role of premarket factors in black-white wage differences. *Journal of political Economy*, 104(5):869–895.

Nyhus, E. K. and Pons, E. (2005). The effects of personality on earnings. *Journal of Economic Psychology*, 26(3):363–384.

Salgado, J. F. (1997). The five factor model of personality and job performance in the european community. *Journal of Applied psychology*, 82(1):30.

Saucier, G. (1994). Mini-markers: A brief version of goldberg's unipolar big-five markers. *Journal of personality assessment*, 63(3):506–516.

Schurer, S., Kassenboehmer, S. C., and Leung, F. (2015). Testing the human capital model of education: Do universities shape their students' character traits?

Sullivan, P. (2010). A dynamic analysis of educational attainment, occupational choices, and job search*. *International Economic Review*, 51(1):289–317.

Summerfield, M., Freidin, S., Hahn, M., Li, N., Macalalad, N., Mundy, L., Watson, N., Wilkins, R., and Wooden, M. (2014). Hilda user manual–release 13.

Terracciano, A., Costa, P. T., and McCrae, R. R. (2006). Personality plasticity after age 30. *Personality and Social Psychology Bulletin*, 32(8):999–1009.

Terracciano, A., McCrae, R. R., and Costa, P. T. (2010). Intra-individual change in personality stability and age. *Journal of Research in Personality*, 44(1):31–37.

Wooden, M. (2013). The measurement of cognitive ability in wave 12 of the hilda survey.

Yamaguchi, S. (2012). Tasks and heterogeneous human capital. *Journal of Labor Economics*, 30(1):1–53.

11 Tables and Graphs

Table 1: Definitions and examples of the ANZSCO coding of occupations

Collar	Occupations	Examples
White Collar	Managers	Legislators, senior officials Corporate/general managers
	Professionals	Professionals, Physician, mathematician, Engineer and life science.
	Technicians and tradespersons	Technicians and associate professionals, Physical and engineering scientists, Life science and health association
Blue Collar	Community and personal service workers	Office clerks, Customer service clerks
	Clerical and administrative workers	Service workers and shop workers, Personal and protective service workers Models, salespersons
	Sales workers	Sales representative, insurance brokers, checkout operator, models and telemarketers,
	Machinery operators and drivers	Industrial spraypainter, sewing machinist, motion picture projectionist, crane operator, forklift driver, and train driver
	Labourers	Cleaners, steel fixer, product assembler, packer, slaughter, farm worker, kitchen hand, freight handler and handypersons

Table 2: The survey illustration of personality questionnaire

B19 How well do the following words describe you? For each word, cross one box to indicate how well that word describes you. There are no right or wrong answers.

*(Cross ☒ **one** box for **each** word.)*

	Does not describe me at all					*Describes me very well*
	1	2	3	4	5	6	7
talkative	1	2	3	4	5	6	7
sympathetic	1	2	3	4	5	6	7
orderly	1	2	3	4	5	6	7
envious	1	2	3	4	5	6	7
deep	1	2	3	4	5	6	7
withdrawn	1	2	3	4	5	6	7
harsh	1	2	3	4	5	6	7
systematic	1	2	3	4	5	6	7
moody	1	2	3	4	5	6	7
philosophical	1	2	3	4	5	6	7
bashful	1	2	3	4	5	6	7
kind	1	2	3	4	5	6	7
inefficient	1	2	3	4	5	6	7
touchy	1	2	3	4	5	6	7
creative	1	2	3	4	5	6	7
quiet	1	2	3	4	5	6	7
cooperative	1	2	3	4	5	6	7
sloppy	1	2	3	4	5	6	7

	Does not describe me at all					*Describes me very well*
	1	2	3	4	5	6	7
jealous	1	2	3	4	5	6	7
intellectual	1	2	3	4	5	6	7
extroverted	1	2	3	4	5	6	7
cold	1	2	3	4	5	6	7
disorganised	1	2	3	4	5	6	7
temperamental	1	2	3	4	5	6	7
complex	1	2	3	4	5	6	7
shy	1	2	3	4	5	6	7
warm	1	2	3	4	5	6	7
efficient	1	2	3	4	5	6	7
fretful	1	2	3	4	5	6	7
imaginative	1	2	3	4	5	6	7
enthusiastic	1	2	3	4	5	6	7
selfish	1	2	3	4	5	6	7
careless	1	2	3	4	5	6	7
calm	1	2	3	4	5	6	7
traditional	1	2	3	4	5	6	7
lively	1	2	3	4	5	6	7

Table 3: Sample summary statistics

Variable	Proportion	Variable	Proportion
Geographic Information		Parental Information	
State		***Father Education***	
NSW	0.3125	College	0.5798
VIC	0.2496	Not College	0.4202
QLD	0.2009	***Mother Education***	
SA	0.0928	College	0.3778
WA	0.0871	Not College	0.6222
TAS	0.0275	***Father Working***	
NT	0.0057	Employed	0.9558
ACT	0.0240	Not Employed	0.0209
Family background		Deceased	0.0233
Family Intactness		***Father Occupation***	
Both parents	0.8341	White Collar	0.6485
Father and step	0.0107	Blue Collar	0.3515
Mother and step	0.0427	***Mother Working***	
Father only	0.0233	Employed	0.5488
Mother only	0.0734	Not Employed	0.4139
Other	0.0158	Deceased	0.0720
Sibling Info		Not Asked	0.0302
Sibling dummy		***Mother Occupation***	
Has siblings	0.9637	Not Asked	0.2113
No siblings	0.0373	White Collar	0.2889
Sibling numbers		Blue Collar	0.4990
Not Asked	0.0379	Cohort Information	
1	0.2563	***Year***	
2	0.3071	1940-1949	0.1038
3	0.1820	1950-1959	0.1919
4	0.0994	1960-1969	0.2358
5 or more	0.1173	1970-1979	0.1913
Eldest Sibling		1980-1989	0.1686
Not Asked	0.0373	1990-	0.1040
Oldest	0.3432		
Not Oldest	0.6195	Total Individuals	4215

Table 4: Personality Traits by Educational Level

Occupation	Emotional Stability	Openness to experience	Conscientiousness	Agreeableness	Extroversion
High School or Lower	-0.0478 (0.0140)	-0.1414 (0.0139)	-.0784 (0.0138)	-0.0508 (0.0141)	0.0393 (0.0133)
College Dropouts	0.0258 (0.0354)	0.0605 (0.0338)	0.1033 (0.0349)	0.0765 (0.0345)	-0.0056 (0.0358)
College Graduates	0.1043 (0.0208)	0.3096 (0.0202)	0.1430 (0.0217)	0.0839 (0.0208)	-0.0997 (0.0232)

Note: Each personality trait has been standardized into mean 0 and variance 1.
Source: HILDA, waves 5, 9 and 13.

Table 5: Personality Traits by Occupations

Occupation	Emotional Stability	Openness to experience	Conscientiousness	Agreeableness	Extroversion
Blue-collar Occupation	-0.0366 (0.0166)	-0.1715 (0.0162)	-.0464 (0.0162)	-0.0208 (0.0168)	0.0215 (0.0158)
White-collar Occupation	0.0797 (0.0166)	0.1507 (0.0164)	0.1360 (0.0171)	0.0573 (0.0164)	-0.0127 (0.0179)

Note: Each personality trait has been standardized into mean 0 and variance 1.
Source: HILDA, waves 5, 9 and 13.

Table 6: Relationship between events intensity and changes in Big-Five Personality

	Extraversion		Agreeableness		Conscientiousness		Stability		Openness	
	Medium-Run	Long-Run	Medium-Run	Long-Run	Medium-Run	Long-Run	Medium-Run	Long-Run	Medium-Run	Long-Run
Education	-0.009 (0.022)	0.005 (0.017)	0.049** (0.023)	0.032* (0.018)	0.022 (0.023)	0.066** (0.018)	0.004 (0.026)	0.017 (0.020)	0.022 (0.023)	0.012 (0.018)
White Collar	-0.002 (0.013)	-0.008 (0.008)	0.007 (0.014)	0.006 (0.008)	-0.012 (0.014)	0.002 (0.008)	-0.010 (0.016)	0.001 (0.009)	0.000 (0.014)	-0.001 (0.008)
Blue Collar	-0.011 (0.014)	−0.016** (0.008)	0.014 (0.015)	0.011 (0.008)	0.003 (0.014)	0.001 (0.008)	-0.016 (0.016)	0.004 (0.009)	-0.013 (0.014)	-0.006 (0.008)
Trend	0.004 (0.056)	0.031 (0.053)	-0.052 (0.060)	0.019 (0.056)	0.078 (0.059)	0.105* (0.057)	0.142** (0.067)	0.090 (0.064)	-0.039 (0.059)	0.044 (0.056)

Note: * means 10% significant level. ** means 5% significant level. Standard errors in parentheses.
Source: HILDA, wave 5, 9 and 13.

Table 7: The impact of of personality and cognitive ability on schooling decisions

	Probit 1	Marginal	Probit 2	Marginal
Emotional Stability	0.084***	0.026	0.057*	0.017
Openness	0.228***	0.070	0.219***	0.066
Conscientiousness	0.137	0.042	0.142***	0.043
Agreeableness	-0.033***	0.010	0.028	0.008
Extraversion	-0.136***	-0.042	-0.150***	-0.045
Cognitive	0.514***	0.157	0.519***	0.157
Family Characteristic	No		Yes	
Observations	6101		4361	
R Square	0.1117		0.1255	

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: The impact of of personality and cognitive ability on occupational decisions

	Pobit1	Mgn1	Pobit2	Mgn2	Pobit3	Mgn3
Emotional Stability	-0.044	-0.015	-0.049	-0.015	-0.074	-0.022
Openness	0.205***	0.072	0.273***	0.093	0.224***	0.066
Conscientiousness	0.122***	0.043	0.103***	0.035	0.083**	0.024
Agreeableness	-0.016	-0.006	0.041	0.014	0.055	0.016
Extraversion	0.042	0.015	-0.012	-0.004	0.030	0.009
Cognitive	0.664***	0.232	0.573***	0.195	0.353***	0.105
College					1.153***	0.401
Family Characteristic	No		Yes		Yes	
Observations	4126		2855		2855	
R Square	0.1142		0.1355		0.2399	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9: The impact of personality and cognitive ability on wage performance

	Blue Collar No College	White Collar No College	Blue Collar College	White Collar College
Emotional Stability	0.022	-0.045	0.024	0.001
Openness	-0.074***	-0.012	-0.078	-0.097***
Conscientiousness	0.085***	0.111***	0.067	0.092***
Agreeableness	-0.040	-0.021	-0.006	-0.046
Extraversion	0.036	0.030	0.113	0.029
Cognitive	0.017	-0.032	-0.041	0.010
Family Characteristic	Yes	Yes	Yes	Yes
Observations	1138	479	223	830
R Square	0.0593	0.0729	0.3095	0.0971

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10: Model parameter estimates: reward functions

	1. *White-Collar*	2. *Blue-Collar*	*3. Schooling*	
	Skill Function		Tuition cost: college	13.5199(0.7885)
Mincer Equation			Additional cost:graduate school	10.6251(0.6737)
Schooling	0.0447(0.0047)	0.0399(0.0052)	Additional utility before age 19	1.5554(0.1181)
White-Collar experience	0.0105(0.0054)	-0.0013(0.0058)	**Constant:**	
Blue-Collar experience	0.0385(0.0048)	0.0244(0.0054)	Type I	8.1760(0.4348)
"Own" experience squared/100	-0.0293(0.0058)	-0.0304(0.0061)	Deviation of type 2	-3.7180(0.0059)
"Own" experience$\times$ edu	0.0103(0.0058)	0.0106(0.0054)	Deviation of type 3	-7.6862(0.0055)
"Own" experience ≤ 2	0.1624(0.0094)	0.2932(0.0185)	Deviation of type 4	-0.8058(0.0058)
Standard Error	0.4750(0.0246)	0.3773(0.0254)	**Family Background**	
Constant:			Family Intactness Dummy	0.0911(0.0060)
Type I	9.8638(0.0684)	9.3990(0.0807)	**Sibling(Omitted cat: only child)**	
Deviation of type 2	-0.0771(0.0058)	0.3893(0.0248)	multiple children, eldest one	-0.1054(0.0065)
Deviation of type 3	-0.6018(0.0061)	-0.3572(0.0063)	multiple($N < 4$), not eldest one	-0.0489(0.0068)
Deviation of type 4	-0.5935(0.0056)	-0.5772(0.0053)	multiple($N \geq 4$), not eldest one	-0.1947(0.0300)
State(Omitted cat:NSW)			**Parental Education(Omitted cat:no college)**	
VIC	-0.1267(0.0056)	-0.1593(0.0057)	One college	0.0750(0.0199)
QLD	-0.0306(0.0062)	-0.5000(0.0055)	Two colleges	0.3830(0.0090)
SA	-0.5045(0.0057)	0.5000(0.0333)	**Cohort(Omitted cat:40-49)**	
WA	0.0135(0.0060)	-0.0044(0.0060)	50-59	-0.1562(0.0058)
TAS	-0.2544(0.0053)	0.5007(0.0298)	60-69	-0.2539(0.0058)
NT	-0.5027(0.0054)	-0.5054(0.0045)	70-79	0.5064(0.0300)
ACT	0.2370(0.0153)	-0.0306(0.0059)	80-89	1.6202(0.0855)
Cohort(Omitted cat:40-49)			After 90	1.6620(0.1557)
50-59	0.1980(0.0134)	0.3038(0.0189)	*4. Home-staying*	
60-69	0.3508(0.0201)	0.4859(0.0250)	Age	0.0138(0.0056)
70-79	0.5334(0.0299)	0.6351(0.0369)	Age squared/100	0.0092(0.0059)
80-89	0.3010(0.0182)	0.5295(0.0305)	**Constant:**	
After 90	0.0003(0.0058)	0.0009(0.0058)	Type I	4.4872(0.1761)
	Non-pecuniary Values		Deviation of type 2	-1.0019(0.0059)
Constant	...	2.3388(0.1145)	Deviation of type 3	-2.2900(0.0055)
College Premium	...	-2.0011(0.1293)	Deviation of type 4	-1.1334(0.0065)
Preference Shock	0.9195(0.0594)		Discount Factor	0.8960(0.0284)

The unit of coefficient under columns of non-pecuniary, school and home-staying has unit 10,000AU$.

Table 11: Estimated coefficients on unobserved type probabilities

Types	I(baseline)	II	III	IV
Constant term	...	0.030	0.001	-0.010
		(.0058)	(.0060)	(.0062)
Cognitive	...	-0.508	-0.990	-1.520
		(.0063)	(.0058)	(.0060)
Openness to Experience	...	-1.500	-1.000	0.000
		(.0067)	(.0064)	(.0051)
Conscientiousness	...	-0.900	-0.520	-1.110
		(.0060)	(.0060)	(.0057)
Extraversion	...	-0.020	-0.026	-0.880
		(.0053)	(.0058)	(.0061)
Agreeableness	...	1.500	0.510	0.510
		(.0968)	(.0285)	(.0295)
Emotional Stability	...	-0.100	-0.110	-0.209
		(.0056)	(.0062)	(.0057)
Parental Background(baseline)				
Middle	0.001	0.007	0.000	-0.010
	(.0065)	(.0058)	(.0058)	(.0066)
High	0.020	0.020	-0.070	0.030
	(.0058)	(.0061)	(.0061)	(.0056)
Family Intactness	0.030	0.020	0.040	0.010
	(.0057)	(.0059)	(.0057)	(.0063)
Persistence of Types	Time shift term		$Age-15$	$\frac{(Age-15)^2}{100}$
Values	0.40		0.12	1.00
	(.0164)		(.0085)	(.0654)

Table 12: Estimated coefficients for the probability of having a change in personality traits

Traits	Edu	$Edu*(Age-15)/100$	$Age-15$	$(Age-15)^2/100$
Openness to Experience	0.0022	-0.0042	-0.0022	0.0116
	(.0056)	(.0056)	(.0060)	(.0055)
Conscientiousness	0.0460	-0.1159	0.0342	-0.0694
	(.0051)	(.0052)	(.0050)	(.0070)
Extraversion	0.0049	-0.0057	-0.0167	0.0384
	(.0058)	(.0058)	(.0055)	(.0055)
Agreeableness	0.0364	-0.0968	0.0086	0.0136
	(.0059)	(.0061)	(.0053)	(.0061)
Emotional Stability	0.0079	-0.0141	0.0108	0.0075
	(.0054)	(.0057)	(.0052)	(.0062)

Table 13: Simulated type proportions for different sector choices

Occupation		Type I	Type II	Type III	Type IV
White-collar	Original	47.89	17.58	9.00	25.53
occupation	Adjusted	43.87	15.05	12.92	24.45
Blue-collar	Original	8.61	48.03	26.47	16.89
occupation	Adjusted	7.89	41.12	38.01	16.18
Schooling	Original	37.53	15.28	4.17	43.03
	Adjusted	34.38	13.08	5.99	41.22
Home staying	Original	7.46	9.17	29.37	54.00
	Adjusted	6.83	7.85	42.17	51.72
Total		27.29	29.20	17.41	26.10

Table 14: Average personality traits and cognitive ability by unobserved type

		Type I	Type II	Type III	Type IV
Openness	Mean	0.466	-0.614	-0.253	0.324
	SE	(0.004)	(0.004)	(0.004)	(0.004)
Conscientiousness	Mean	0.453	-0.274	0.069	-0.406
	SE	(0.004)	(0.004)	(0.005)	(0.004)
Extraversion	Mean	0.289	0.113	0.168	-0.427
	SE	(0.004)	(0.004)	(0.005)	(0.004)
Agreeableness	Mean	0.300	-0.201	0.002	-0.059
	SE	(0.004)	(0.004)	(0.005)	(0.004)
Stability	Mean	0.127	0.022	0.088	-0.318
	SE	(0.004)	(0.004)	(0.005)	(0.004)
Cognition	Mean	0.473	-0.165	0.056	0.011
	SE	(0.004)	(0.004)	(0.005)	(0.004)

Table 15: Determinants of ex-ante utility variation

	Reg 1	Reg 2	Reg 3
Intactness	−0.814*	−0.612	−0.579
Father Occupation	0.476	0.264	0.300
Parental Education	0.546**	0.284	0.235
Sibling	−0.417**	−0.337*	−0.297*
Cohort	1.454***	1.452***	1.406***
State	0.850***	0.844***	0.836***
Cognitive		2.080***	1.975***
Openness			0.245
Conscientiousness			1.210***
Extraversion			0.905***
Agreeableness			0.347*
Emotional Stability			−0.234
Observation	4215	4215	4215
R square	0.095	0.121	0.154

Table 16: Model specification test

	Baseline model	"Fixed type" model
Null Hypothesis		H0: $P_a = 0, \gamma_{4kn} = 0$
Distance Measure	2279.976	2406.325
LR test		126.349
The number of restrictions		18
$\chi^2(0.01)$ criteria		34.80

Table 17: The effect of college subsidy and compulsory senior secondary school policies among types

Baseline Model	Type I	Type II	Type III	Type IV	Total
Percentage of Finishing High school					
Benchmark	98.4%	78.4%	75.5%	97.9%	88.2%
50% college subsidy	0.2%	0.5%	0.5%	0.2%	0.2%
Compulsory senior secondary school	1.6%	21.6%	24.5%	2.1%	11.8%
Percentage of College Graduates					
Benchmark	43.6%	19.5%	21.8%	43.9%	32.4%
50% college subsidy	32.1%	19.1%	21.6%	28.3%	25.2%
Compulsory senior secondary school	0.5%	1.9%	4.2%	0.8%	1.7%
Education Years					
Benchmark	14.347	12.132	12.072	14.832	13.431
50% college subsidy	1.003	0.593	0.687	0.924	0.799
Compulsory senior secondary school	0.031	0.477	0.635	0.051	0.279
Annual Earning(for workers)					
Benchmark	96852.8	71946.8	34145.8	44211.4	66324.1
50% college subsidy	6672.8	2389.8	2340.0	8208.7	4718.7
Compulsory senior secondary school	606.2	3616.2	2804.3	451.0	2210.4
Utility Change(Unit: AU$10,000)					
Benchmark	80.132	73.908	68.623	73.786	74.520
50% college subsidy	1.758	0.574	0.687	0.477	1.135
Compulsory senior secondary school	-0.831	-3.434	-5.328	-0.882	-2.423
Personality Traits at age 30					
Openness to experience					
Benchmark	0.458	-0.634	-0.262	0.319	-0.018
50% college subsidy	0.002	-0.001	0.003	0.001	0.001
Compulsory senior secondary school	-0.007	0.003	0.005	0.000	0.001
Conscientiousness					
Benchmark	0.388	-0.357	-0.008	-0.450	-0.113
50% college subsidy	0.031	0.010	0.017	0.034	0.026
Compulsory senior secondary school	0.000	0.027	0.020	0.001	0.015
Extraversion					
Benchmark	0.338	0.144	0.212	-0.374	0.075
50% college subsidy	0.003	-0.001	-0.002	0.004	0.004
Compulsory senior secondary school	0.007	-0.008	0.004	-0.001	0.002
Agreeableness					
Benchmark	0.251	-0.279	-0.058	-0.103	-0.048
50% college subsidy	0.024	0.012	0.005	0.030	0.020
Compulsory senior secondary school	0.005	0.016	0.018	0.003	0.011
Emotional Stability					
Benchmark	0.027	-0.073	0.003	-0.406	-0.118
50% college subsidy	0.001	0.009	-0.008	0.008	0.005
Compulsory senior secondary school	0.002	0.001	0.012	-0.006	0.003

Table 18: Policy effects under restricted "fixed types" model

"fixed types" model	Type I	Type II	Type III	Type IV	Total
Percentage of Finishing High school					
Benchmark	100.0%	73.6%	41.2%	100.0%	81.8%
50% college subsidy	0.0%	0.0%	0.0%	0.0%	0.0%
Compulsory senior secondary school	0.0%	26.4%	58.8%	0.0%	18.2%
Percentage of College Graduates					
Benchmark	55.8%	0.2%	0.0%	77.1%	34.9%
50% college subsidy	35.0%	8.3%	0.0%	17.0%	15.9%
Compulsory senior secondary school	0.8%	0.0%	0.0%	1.2%	0.5%
Education Years					
Benchmark	14.637	11.813	10.993	15.409	13.354
50% college subsidy	1.053	0.249	0.004	0.547	0.487
Compulsory senior secondary school	0.023	0.484	1.150	0.039	0.361
Annual Earning(for workers)					
Benchmark	100481.5	69533.0	29793.3	47273.6	66004.0
50% college subsidy	4656.1	909.5	9.4	7232.8	2943.7
Compulsory senior secondary school	484.9	2390.3	2565.4	760.0	1592.8
Utility Change(Unit: AU$10,000)					
Benchmark	83.971	77.209	53.354	65.214	71.559
50% college subsidy	2.504	0.064	0.000	2.246	1.251
Compulsory senior secondary school	-0.261	-2.196	-4.386	-0.396	-1.597

Table 19: The effect of education policies on type proportions at different ages

Age		Type I	Type II	Type III	Type IV
15	Benchmark	24.70	31.44	16.89	26.98
	50% college subsidy	24.70	31.44	16.89	26.98
	Compulsory senior secondary school	24.70	31.44	16.89	26.98
18	Benchmark	24.93	31.03	17.11	26.93
	50% college subsidy	24.93	31.03	17.11	26.93
	Compulsory senior secondary school	25.10	30.91	17.22	26.76
21	Benchmark	26.14	30.06	16.84	26.95
	50% college subsidy	26.19	30.04	16.92	26.86
	Compulsory senior secondary school	26.43	29.94	17.13	26.50
24	Benchmark	26.62	29.18	17.67	26.52
	50% college subsidy	26.81	29.09	17.79	26.31
	Compulsory senior secondary school	26.93	28.99	17.94	26.14
27	Benchmark	27.45	28.94	17.39	26.22
	50% college subsidy	27.69	28.75	17.58	25.98
	Compulsory senior secondary school	27.73	28.78	17.58	25.91
30	Benchmark	27.69	28.92	17.46	25.93
	50% college subsidy	27.95	28.75	17.67	25.62
	Compulsory senior secondary school	27.97	28.75	17.60	25.67
> 33	Benchmark	27.83	28.78	17.53	25.86
	50% college subsidy	28.09	28.61	17.77	25.53
	Compulsory senior secondary school	28.11	28.61	17.67	25.60

Table 20: The effect of college subsidy and compulsory senior secondary school policies among different SES

	Social Economic Status			
Baseline	I	II	III	Total
Percentage of Finishing High school				
Benchmark	84.7%	87.9%	91.8%	88.1%
50% college subsidy	0.3%	0.2%	0.4%	0.3%
Compulsory senior secondary school	15.3%	12.1%	8.2%	11.9%
Percentage of College Graduates				
Benchmark	25.4%	30.2%	41.6%	32.4%
50% college subsidy	25.1%	26.9%	23.5%	25.3%
Compulsory senior secondary school	0.9%	2.1%	1.9%	1.7%
Education Years				
Benchmark	13.081	13.346	13.865	13.431
50% college subsidy	0.778	0.854	0.756	0.799
Compulsory senior secondary school	0.324	0.301	0.210	0.278
Annual Earning(for workers)				
Benchmark	62861.9	66433.2	69580.6	66324.1
50% college subsidy	4410.2	4860.8	4869.0	4718.7
Compulsory senior secondary school	2148.4	2434.2	2000.8	2210.4
Utility Gain(Unit: AU$10,000)				
Benchmark	73.135	74.380	76.014	74.500
50% college subsidy	0.878	1.091	1.434	1.155
Compulsory senior secondary school	-2.812	-2.426	-2.044	-2.403
Personality Traits at age 30				
Openness to experience				
Benchmark	-0.180	0.019	0.138	-0.018
50% college subsidy	0.002	-0.036	0.002	0.001
Compulsory senior secondary school	0.001	-0.037	0.001	0.001
Conscientiousness				
Benchmark	-0.128	-0.127	-0.084	-0.113
50% college subsidy	0.025	0.028	0.025	0.026
Compulsory senior secondary school	0.017	0.016	0.011	0.014
Extraversion				
Benchmark	0.037	0.066	0.121	0.075
50% college subsidy	0.003	0.004	0.004	0.004
Compulsory senior secondary school	0.002	0.003	0.002	0.002
Agreeableness				
Benchmark	-0.098	-0.063	0.019	-0.047
50% college subsidy	0.018	0.021	0.020	0.020
Compulsory senior secondary school	0.013	0.012	0.009	0.011
Emotional Stability				
Benchmark	-0.194	-0.102	-0.064	-0.118
50% college subsidy	0.006	0.006	-0.005	0.005
Compulsory senior secondary school	0.003	0.003	0.001	0.002

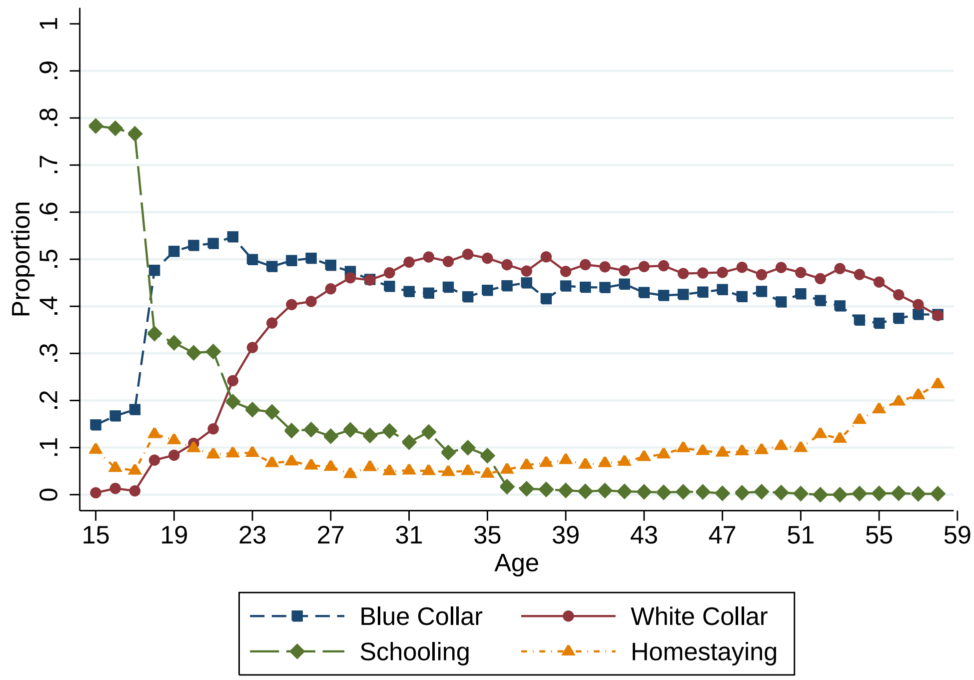


Figure 1: Work status and college attendance by age(% of the sample)

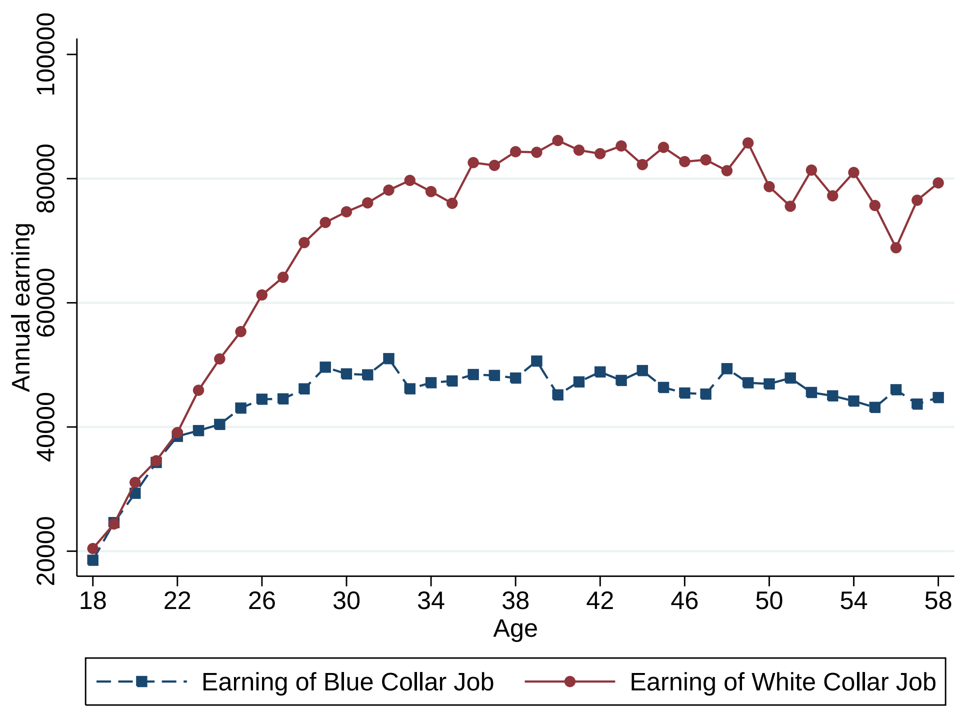
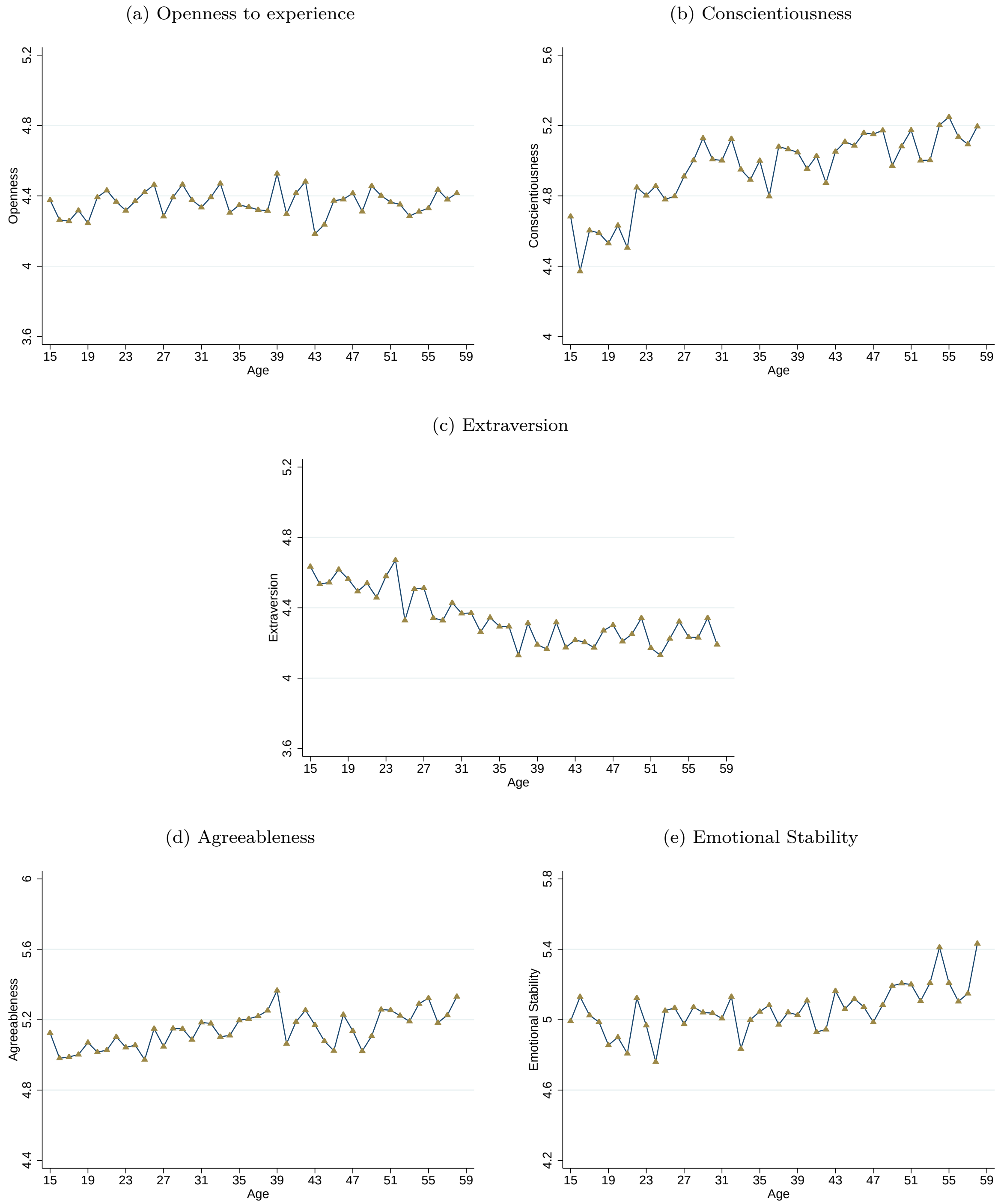


Figure 2: Average wage profile by occupations over life cycle

Figure 3: The scores of “Big-Five” personality traits over time



(a) Openness to experience

(b) Conscientiousness

(c) Extraversion

(d) Agreeableness

(e) Emotional Stability

Source: HILDA, wave 2013.

Figure 4: The probability of type change by age

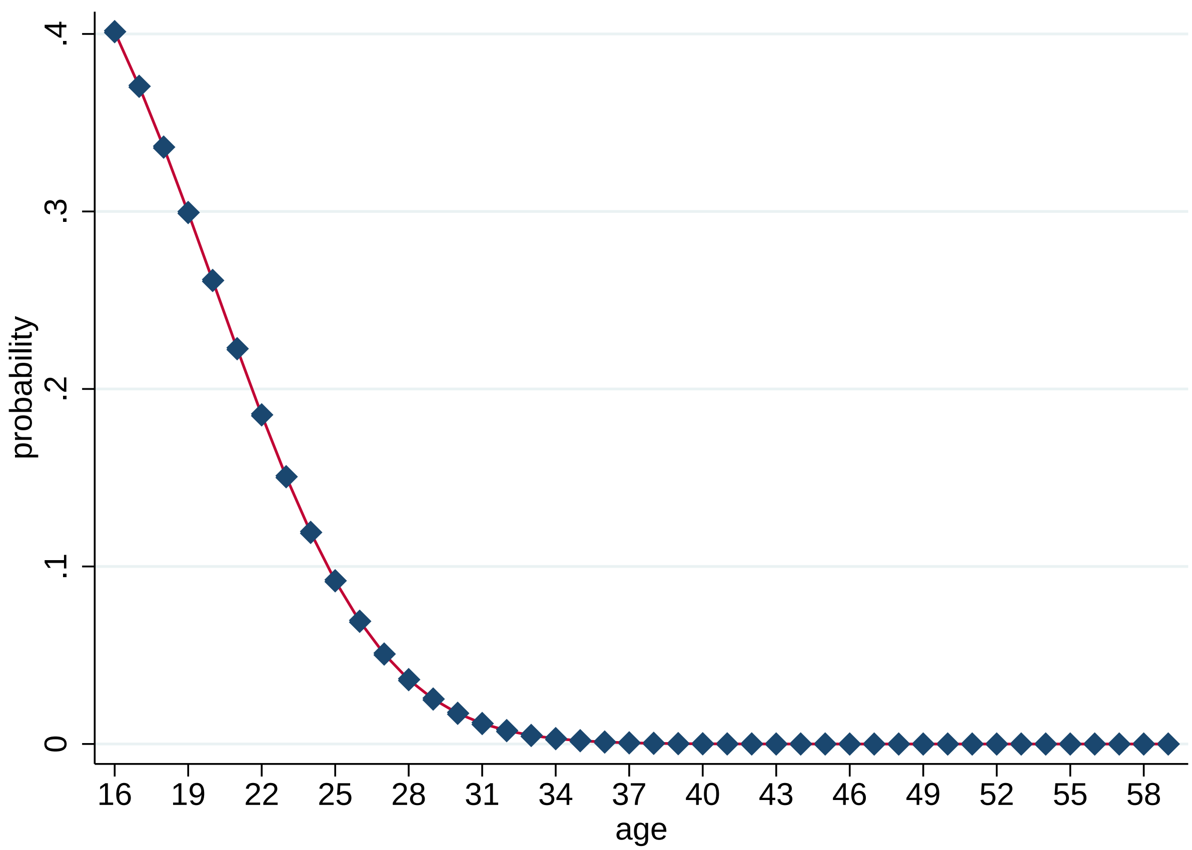


Figure 5: The comparison of choice distribution and earning profile between real data and model simulations

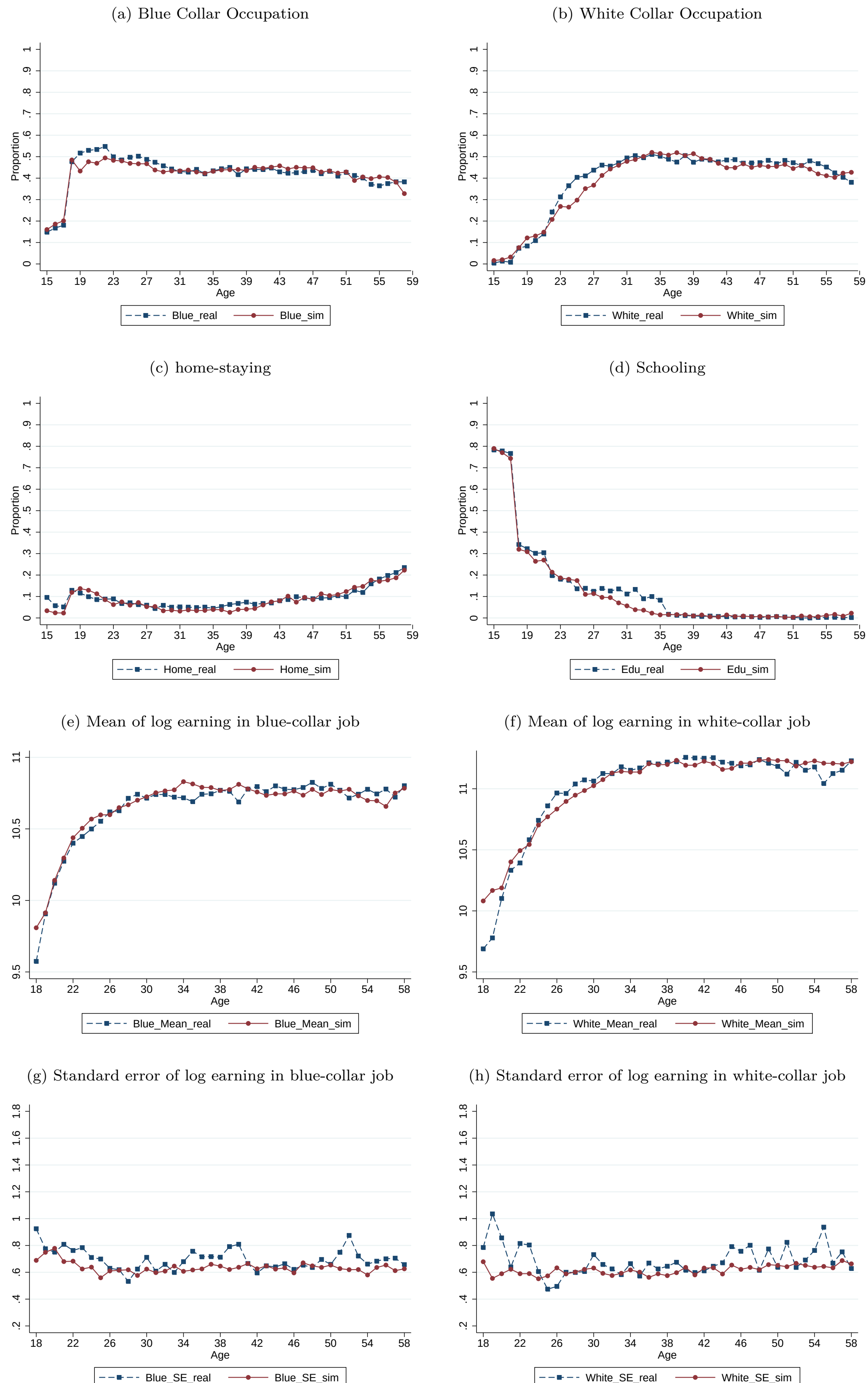
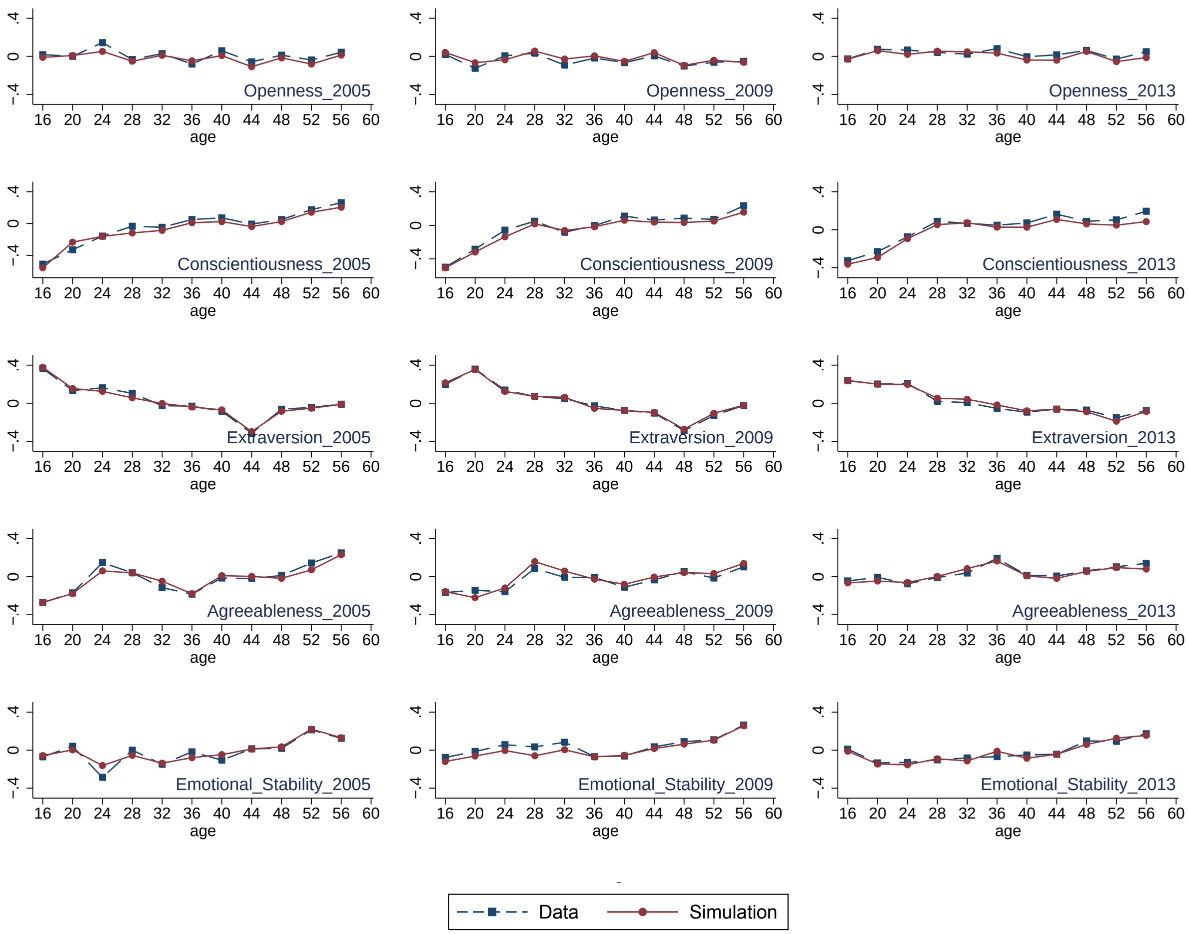


Figure 6: The comparison of personality traits between real data and model simulations



Data Source: "Big-Five" personality traits gathered in wave 2005, 2009 and 2013.

Figure 7: Average personality traits of each type

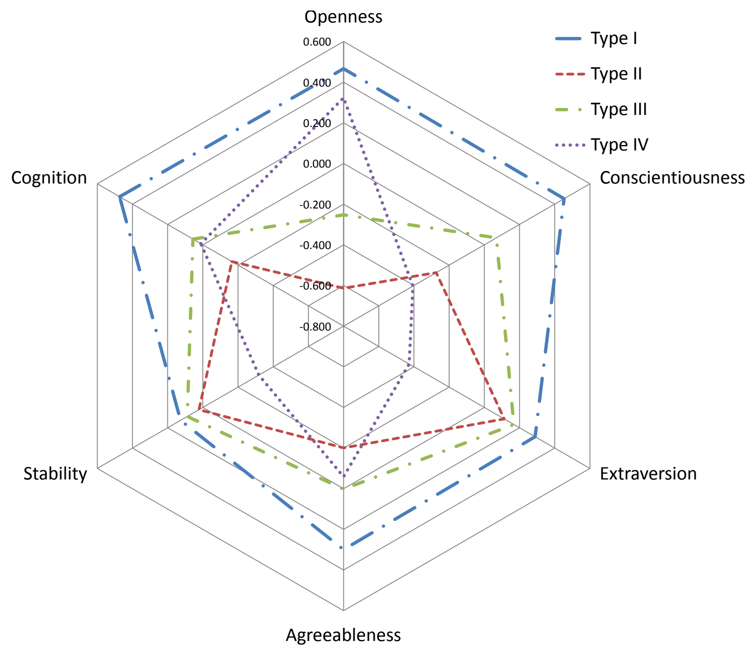
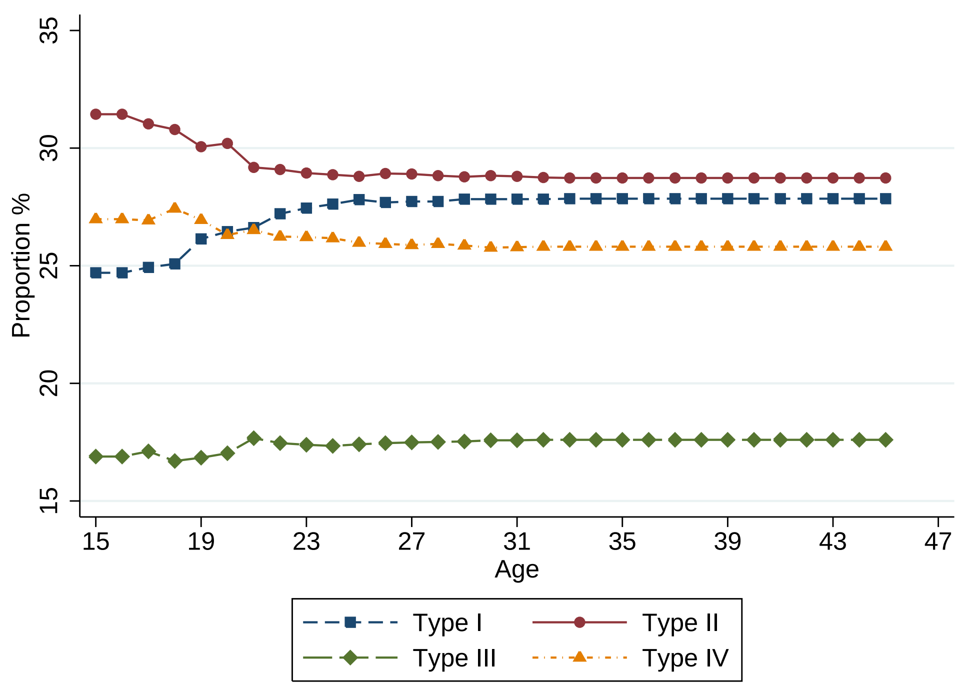


Figure 8: The fraction of types by age cohort



Appendices

A Method used to impute initial age 15 personality traits

In many cases, sampled individuals are older than age 15, so we do not directly observe initial personality traits. The data contain up to three measures of personality traits, each measured at a time four years apart. We next describe the method that we use to impute the initial personality traits $\theta_n(15)$ based on these three measures, $\theta_n^{M1}(a_1), \theta_n^{M2}(a_2), \theta_n^{M3}(a_3)$, observed at ages a_1, a_2, a_3 and using the structure of our model. Given the current trial parameter values Ω, personality trait n at age 15 ($\theta_n(15)$) is obtained as follows:

1. From equation (2) in subsection 4.1, we solve for

$$\theta_n(a_1 - 1) = \theta_n(a_1) - (\gamma_{0n} + \gamma_{1n}(a_1 - 1 - 15) + \gamma_{2n} d_3(a_1) + \gamma_{3n}(a_1 - 1 - 15) d_3(a_1))$$

   where a_1 is the age when individual is surveyed and $d_3(a_1)$ is the indicator whether the individual is in school (alternative $m = 3$) at age a_1.

2. Substituting $\theta_n(a_1) = \theta_n^{M1}(a_1) - \zeta_n(a_1)$, we get

$$\theta_n(a_1 - 1) + \zeta_n(a_1) = \theta_n^{M}(a_1) - (\gamma_{0n} + \gamma_{1n}(a_1 - 16) + \gamma_{2n} d_3(a_1) + \gamma_{3n}(a_1 - 16) d_3(a_1))$$

3. Given $\theta_n(a_1 - 1) + \zeta_n(a_1)$, recover $\theta_n(a_1 - 2) + \zeta_n(a_1)$ following the same approach.

$$\theta_n(a_1 - 2) + \zeta_n(a_1) = (\theta_n(a_1 - 1) + \zeta_n(a_1)) - (\gamma_{0n} + \gamma_{1n}(a - 17) + \gamma_{2n} d_3(a_1 - 1) + \gamma_{3n}(a_1 - 17) d_3(a_1 - 1))$$

   Continue this way until we get $\theta_n^{M1}(15) \equiv \theta_n(15) + \zeta_n(a_1)$.

4. For the other two personality measurements at age a_2 and age a_3, ($\theta_n^{M2}(a_2)$ and $\theta_n^{M3}(a_3)$), repeat steps (1)-(3) to get

$$\theta_n^{M2}(15) \equiv \theta_n(15) + \zeta_n(a_2)$$

$$\theta_n^{M3}(15) \equiv \theta_n(15) + \zeta_n(a_3)$$

5. This procedure provides three different imputed values of initial personality traits, each with a measurement error that is assumed to be mean zero. We obtain our measure of the personality trait at age 15 $\theta_n(15)$ as the mean of these three values:

$$\theta_n(15) = \frac{1}{3}(\theta_n^{M1}(15) + \theta_n^{M2}(15) + \theta_n^{M3}(15))$$