A Dynamic Model of Personality, Schooling, and Occupational Choice

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Abstract

This paper develops a dynamic model of schooling and occupational choices that incorporates personality traits, as measured by the so-called "big five" traits. The model is estimated using the longitudinal HILDA 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 trait scores. 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 heterogeneity in how people respond to educational policies.

JEL: C54, J24, I24, I28

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

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1 Introduction

Cognitive skills are known to be 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 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 skills, as measured by the so-called "big five" personality traits. 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 model without personality traits.

A key finding of Keane and Wolpin (1997) is that 90 percent of the total variance in expected lifetime utility is explained by unobserved skill endowments at age 16. Other studies also emphasize the importance of unobserved heterogeneity. 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% 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% of the variation in lifetime earnings and 64% of the variation in lifetime utility is attributable to initial conditions.

Although accumulated evidence points to endowment heterogeneity as being important 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 adding 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 in estimation do not include 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 psychology (Goldberg (1992);Saucier (1994);Gosling et al. (2003)). 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. In economics, there are some studies that consider the role of the "big-five" in explaining wage, employment, education and marriage outcomes.

However, there are no existing studies that introduce personality traits within a modeling framework in which these outcomes are jointly determined. Also, the few dynamic life-cycle models in the literature that incorporate noncognitive traits usually represent traits using a single factor model and do not use a multidimensional traits.[1].

The goals of this paper are: (i) to incorporate the "big-five" personality traits within a dynamic life-cycle framework model of education and employment choices (ii) to explore the role of personality traits as determinants of unobserved heterogeneity, and (iii) to use the modeling framework developed to evaluate both the mean and the distributional effects of educational policies.

To achieve these aims, we estimate a dynamic model of schooling, work and occupational choices that assumes that individuals ages 15 to 50 make one of four mutually exclusive choices: attending school, staying home, working in a white-collar job or working in a blue-collar job. To lessen the computational burden, we assume that after age 50 individuals stay in their most recent sector choice until retirement (age 65). 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 can affect their pecuniary and nonpecuniary reward from choosing particular schooling or work options.

We incorporate the “big five" personality traits into the model in a parsimonious way as a determinant of the unobserved type probabilities. Personality traits are observed to change over time and to be influenced by school attendance. We therefore allow individual's unobserved types to potentially change over time. In the dynamic discrete choice literature, the standard approach is to assume fixed types (e.g. Keane and Wolpin (1997), Yamaguchi (2012), Sullivan (2010)). However, methodological papers by Hu et al. (2015) and Arcidiacono and Miller (2011) consider the use of time-varying types that follow a Markov process. We adopt a similar type of specification and implement a likelihood ratio test for type stability, which is rejected in our data.

We estimate our model using the Household Income and Labour Dynamics in Australia (HILDA) longitudinal data, waves 1(2001) through 13(2013). The data have repeated measures of personality traits as well as measures of cognitive ability. The estimation results show that the unobserved types are malleable, particularly at early ages. At age 15, individuals have on average a 75% probability to change type, but by age 30 their type stabilizes. Our 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 compul-

[1]e.g. (Borghans et al. (2008))

sory and providing a 50% cost subsidy to attend college. Both policies provide incentives to enroll in school but they differ in their distributional implications. We find that individuals belonging to types I and IV have a comparative advantage in education and 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.

To study the relevance of time-varying heterogeneity and personality traits in assessing impacts of educational policies, we also estimate a version of our model with fixed types in the spirit of Keane and Wolpin (1997). In the fixed type model, there is less incentive for disadvantaged groups to pursue education, because they no longer have the potential to alter their disadvantaged types. The increase in annual earnings and the effect on educational attainment attributable to the policy intervention is significantly smaller in the fixed type model. Moreover, the distribution of policy impacts is more unequal 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 big five measures. Section IV describes the model. Section V discusses the identification strategy and section VI explains the estimation strategy. Section VII presents the estimation results and provides information for the goodness of model fit. Section VIII . Section IX reports results from the two policy experiments and section X concludes.

2 Related Literature

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 a few papers that examine the correlation between personality traits and educational attainment. For example, Lundberg (2013) finds positive correlations between personality traits (such as conscientiousness, agreeableness and openness to experience) and college entrance. Dahmann and Anger (2014) and Schurer et al. (2015) note that educational experiences in secondary school and at university shape students' personalities.

Our paper is also related to the burgeoning literature examining the process of non-cognitive skill formation. Heckman et al. (2006) study the effect of non-cognitive skills on schooling decisions and subsequent labour market outcomes.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

Our 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 survey starting from the year 2001 with 19,914 initial individuals from 7,682 households. (Summerfield et al. (2014)) We make use of the following variables: (1) labor market outcomes including occupational information (coded following the ANZSCO system[2]), 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.[3] 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), 28 of the 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. The other 28 items, on the other hand, are noisy

[2]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 as well as clerical and administrative workers. Blue collar jobs include community and personal service workers, sales workers, machinery operators and drivers as well as labourers. See table 1 for details.

[3]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.

measures of a single trait.[4] The big five personality traits are available for 4,938 males interviewed in wave 5 and for 5,048 and 6,771 male respondents in waves 9 and 13. We include in our analysis all individuals who have at least one measure of personality traits.

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.

*** HOW??***

3.1 Additional background variables and sample restrictions

In addition to the cognitive and noncognitive trait measures described above, we use the following family background 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 status.[6] We also include state of residence and cohort information.

Our estimation focuses on males between age 15-44. Women are not included to avoid additional complication of modeling marriage and fertility decisions, which may impact schooling and labor supply decisions. Individuals serving in the military are also excluded. 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 total.

Selected summary statistics of individual's characteristics are reported in table 3. Our sample is distributed across eight states and territories. Most individuals (>95%) have siblings. Approximately one-third are the eldest child in the family. Table 3 also provides statistics on parental education and occupations at the time the individual was age 14. Almost two-thirds of fathers have a college degree while only a half mothers have a college degree. Most fathers were employed (>95%), but only about two-thirds of the sample had working mothers (64%). The majority of fathers' jobs were in white-collar occupations (72%), whereas 53% of the working mothers worked in white-collar jobs. The majority of individuals (80%) report residing with of their parents at the age of 14.

[4] Openness to experience is constructed by scores from six adjective items including imaginative, creative, intellectual, philosophical, deep and complex. Conscientiousness is is constructed by scores from six adjective items including orderly, disorganised, efficient, sloppy, inefficient and systematic. Extraversion is constructed by scores from six adjective items including quiet, shy, talkative, extroverted, bashful and lively. Agreeableness is constructed from scores from four items including warm, kind, sympathetic and cooperative. And lastly, emotional stability is constructed from six items including moody, temperamental, jealous, fretful, envious and touchy. An analysis how the each personality is constructed using factor analysis are detailed in Losoncz (2009).

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

[6] All the parental questions pertain to when the respondent was age 14.

3.2 Educational and occupational choices over life cycle

In the HILDA survey, individuals report both school enrollment and employment information annually.[7] 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, almost everyone is enrolled in school but after age 19, this fraction drops sharply to around 35%. The majority of secondary school graduates choose to work immediately rather than to continue their tertiary education. The school enrollment rate keeps decreasing from 20% at age 23 to around 3% at age 27.

We define an individual to be "working" if reported to be working positive hours and not enrolled in school.[8] An individual is defined to be "staying home" if he is neither working nor in school.[9] The blue-collar participation rate increases dramatically to around 30% at age 18. It stabilizes at around 40% after that. The significant increase in 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. The percentage staying home increasing shortly after graduation from secondary school graduation and then declines to roughly 5%.

Figure 2 reports the age-earnings profile by blue collar or white collar occupations, between ages 18 to 44.[10]. Thus their choices is classified as schooling according to our definition. Both the white-collar and blue-collar earnings profiles exhibit a concave increase, 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. Peak average earnings from blue-collar jobs is around AU$58,000, whereas the peak from white-collar jobs is around AU$99,000.

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. College graduates have higher average scores on emotional stability, openness to experience, conscientiousness, and agreeableness. However, this group tends to be less extraverted.

[7] 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.

[8] A small fraction of individuals report working and attending schools simultaneously. When it happens, we record an individual as schooling if his age is less than 25 and recorded as working if his age is larger or equal than 25.

[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 do not include wage observations between age 15 and age 17, because a large fraction of this age group attends school and works part-time

Table 5 reports the difference in personality traits between white-collar and blue-collar workers. White-collar workers have higher average scores on emotional stability, openness to experience, conscientious, and aggreableness. The greatest differences in scores by occupation sector are seen in conscientiousness and openness to experience.

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 that personality traits change with age, 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. Figures 3(a) to 3(e) show the average score on the "big five" over the life cycle using the 2013 data wave. Compared with the other traits, openness to experience exhibits greater stability. Conscientiousness, agreeableness and emotional stability increase with age. Extraversion decreases with age until age 35, and then stays stable. Overall, traits appear to be more malleable for younger respondents.

3.4 Correlation between personality traits, schooling and occupation sector

We now investigate how working and schooling correlates with observed changes in personality (table 6). After standardizing the scores to each have mean 0 and variance 1, we estimate fixed effects models of personality traits on education, age, age squared, age interacted with education and indicators for whether the individual is in a white or blue collar occupation. Each column of table 6 reports the estimation results for a different trait. The coefficients associated with regressors involving age and education are statistically significantly different from zero for three out of the five traits (openness, conscientiousness and emotional stability), indicating that personality traits vary with age and with school attendance. The occupational sector does not have any relationship with personality traits (conditional on the fixed effects).

Table 7 shows the relationship between log earnings, personality traits and cognitive ability. The specification is analogous to a Mincer log earnings regression (estimated for individuals with positive earnings). The first column presents estimates where the included variables are education, potential experience and potential experience-squared.[11]. The so-called "rate of return" to education is around 11%.[12] The second column adds personality traits to the specification. All of the traits have associated coefficients that are statistically different from zero. The most important trait for increasing earnings is conscientiousness. Three

[11]Potential experience is defined as age - years of education - 6

[12]It is relatively high, in part because the sample is restricted to individuals age 17-44. The estimated rate of return is lower when older age individuals are included.

of the traits (openness, emotional stability, and agreeableness) have, ceteris paribus, negative effects on earnings. The regression also includes cognitive ability (standardized to have mean zero and variance 1). Ceteris paribus, a one standard deviation increase in cognitive ability increases earnings by 7-8 percent. The third column adds to the specification a set of family background variables as additional control variables (described in the table notes). The estimated coefficients on all the variables change little when the family background variables are added, although the R-squared increases.

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 44. At each age, individuals maximize their remaining discounted lifetime utility. The terminal age is 65 but to facilitate computation, we assume that individuals make choices until age 44 and then stay in their age 44 sector choice from ages 45-65. 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 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. As noted in the introduction, one important aspect of our model that deviates from most of the 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.[13]

We use $\Theta(a)$ to represent personality traits and $k(a)$ to denote the unobserved type at age a, assumed to be known by the individual but not by the econometrician. $s_o(a)$ 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 previous period type $k(15)$.

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

[13] Arcidiacono and Miller (2011) and Hu et. al. (2015)

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. We assume that the true $n-th$ personality trait $\theta_n \in \Theta, \{n = 1,2,3,4,5\}$ is measured with error and denote the measurement error shock as $\zeta_n(a)$. We adopt the following specification for the evolution of each trait:

$$\begin{aligned} \theta_n^M(a) &= \theta_n(a) + \zeta_n(a) \\ \theta_n(a) &= \theta_n(15) + \gamma_{0n} + \gamma_{1n} g(a) + \gamma_{2n}(a-15)g(a) + \gamma_{3n}(a-15) + \gamma_{4n}(a-15)^2 \end{aligned} \tag{2}$$

where $\theta_n^M(a)$ is the measure of the nth personality trait at age a and $\theta_n(a)$ is the true trait without measurement error. γ_{3n} and γ_{4n} capture the linear and quadratic terms of age effects. The term $\gamma_{1n} + \gamma_{2n}(a-15)$ captures the potential effect of education on personality traits.

As previously noted, we allow the unobserved types to change in a way that may depend on age and on personality characteristics. We specify a Markov process for the evolution of the discrete types. After the initial period, the type $k(a)$ can stay the same with probability $1 - p(a)$ or change with probability $p(a)$.[14] 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:

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

where

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

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

[14]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.

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

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 shows how the type probability may depend on personality traits $\theta_n(a)$ and 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 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:

$$\begin{aligned} e_m(a) = exp(e_m^k + \sum_{i=1}^{I} \beta_{m0i} d_i + \beta_{m1} g(a) + (\beta_{m2} + \beta_{m3} I\{x_m(a) \leq 2\}) x_m(a) \\ + \beta_{m4} x_m^2(a) + \beta_{m5} x_m(a) g(a) + \beta_{m6} c + \xi_m(a)) \end{aligned} \tag{8}$$

which yields a log-wage equation the form:

$$\begin{aligned} \log w_m(a) = \log p_m + e_m^k + \sum_{i=1}^{I} \beta_{m0i} d_i + \beta_{m1} g(a) + (\beta_{m2} + \beta_{m3} I\{x_m(a) \leq 2\}) x_m(a) \\ + \beta_{m4} x_m^2(a) + \beta_{m5} x_m(a) g(a) + \beta_{m6} c + \xi_m(a) \end{aligned} \tag{9}$$

In (9), $d_i, i \in \{state \times cohort\}$ is a fixed effect for 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 work 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. The component $\beta_{m6}c$ captures the return to cognitive abilities. $\xi_m(a)$ is a skill technology shock, which is assumed to be 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.

$$
\begin{aligned}
&r_1(a) = 0 \\
&r_2(a) = \beta_7 + \beta_8 I[g(a) \leq 12]
\end{aligned} \tag{10}
$$

If a person chooses to attend school, the per-period utility consists of two parts: a nonpecuniary component, which may reflect any physical and mental costs when attending school, and a pecuniary component, such as tuition costs and fees. The utility associated with school attendance at age a is:

$$
\begin{aligned}
u_3(a) = e_3^k + \sum_{z=1}^{Z} \alpha_z d_z + \sum_{r=1}^{R} \alpha_r d_r + \alpha_c c + \alpha_0 I(age < 18) - \alpha_1 I(college) \\
- \alpha_2 I(graduate) + \epsilon_3(a)
\end{aligned} \tag{11}
$$

The indicators d_z capture the effects of family background on a person's preference for attending school.[15] d_r is a cohort-specific effect, and c is the effect of cognitive ability on the education choice. The term $\alpha_0 I(age < 18)$ captures the extra utility of attending school when the agent is under the age 18. α_1 and α_2 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 preference shock $\epsilon_4(a)$, i.e.:

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

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.[16] Different types have different type-

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

[16] Each of the five traits can take values 1 through 7. The structure we assume avoids the include a five-dimensional personality trait vector in the time-varying state space. However, the initial personality traits are included in the state space. The traits evolve deterministically over time according to equation 2 and are assumed to be measured with error.

specific components e_m^k for each choice m.

4.3 Information structure

In our model, individual heterogeneity comes from two sources: ex-ante endowments $\{k(15), \Theta(15), c, Z, state, cohort\}$[17] at age 15 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). The key identification assumption in their paper is the "limited feedback" restriction, namely that (1) the choice at age a $\Pr(d_m(a)$ is independent of variables from last period $a-1$ after conditioning on the state variables at age a: $\Pr(d_m(a)|s_{-k}(a), k(a), s_{-k}(a-1), k(a-1), d_m(a-1)) = \Pr(d_m(a)|s_{-k}(a), k(a))$, where $s_{-k}(a)$ represents all the other state variables besides types $k(a)$. (2) the type evaluation $k(a)$ is independent of choices from last period $d_m(a-1)$ conditioning on other state variables

[17]The other three state variables are constant values for every individual at age 15. $g(15) = 0, x_1(15) = 0, x_2(15) = 0$.

in current period and all state variable in last period: $\Pr(k(a)|s_{-k}(a), s_{-k}(a-1), k(a-1), d_m(a-1)) = \Pr(k(a)|s_{-k}(a), s_{-k}(a-1), k(a-1))$. Following Hu et al. (2015), the Markov transition matrix can be factored into three terms:

$$\begin{aligned} &\Pr(d_m(a), s_{-k}(a), k(a)|d_m(a-1), s_{-k}(a-1), k(a-1)) \\ = &\underbrace{\Pr(d_m(a)|s_{-k}(a), k(a))}_{\text{CCP}} \underbrace{\Pr(k(a)|s_{-k}(a), s_{-k}(a-1), k(a-1))}_{\text{Law of motion for type k}} \underbrace{\Pr(s_{-k}(a)|d_m(a-1), s_k(a-1), k(a-1))}_{\text{Law of motion for } s_{-k}} \end{aligned}$$

Hu et al. (2015) shows that the right three terms can be identified by the observations from at least three periods $\{d_m(a), s_{-k}(a), d_m(a-1), s_{-k}(a-1), d_m(a-2)\}$. Detailed discussion of how to extend their results to our context can be found in Appendix.[18]

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 collar 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 identify from the data 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 the unobserved type $k(a)$.[19] 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

[18] 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.

[19] 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 .2.

possible sequences of future choices given the current state space:

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

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.
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 model that the sector is chosen after preference shocks are realized but before the wage shock is realized. We denote $\tilde{u}_m(s(a), a)$ as $u_m(s(a), a)$ 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. [20]

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

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

[20]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.

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

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

where γ is the Euler's constant and σ_c is the scale parameter of the preference shock.[21]

The dynamic programming problem uses 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, which are part of the model's state space, are not directly observed and therefore need to be simulated from initial conditions.

The simulation process is 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 .2. Initial unobserved types $k(15)$ are drawn from equation 5.

3. Starting from $s(15)=g(15)=0, x_i(15)=0, k(15), \theta_n(15)$, 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

[21] 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).

weighted difference between those R simulated moments $\tilde{M}_{N,R}(\Omega)$ and the data moments M_R, using the following objective criterion:

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

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.[22]

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, $plim_{N\to\infty}\tilde{M}_{N,R}(\Omega_0) = M_R(\Omega_0)$.[23] In total, we match 298 moments to estimate 118 parameters. The following moments are used in estimation:

1. Sequential life-time choices (120 moments)
   - The fraction of individuals in the blue-collar occupation sector by age (15-44).
   - The fraction of individuals in the white-collar occupation sector by age (15-44).
   - The fraction of individuals in school by age (15-44).
   - The fraction of individuals at home by age (15-44).
2. Earning profiles (108 moments)[24]
   - Average log earnings of blue-collar workers by age (18-44).
   - Average log earnings of white-collar workers by age (18-44).
   - The standard deviation of log earnings of blue-collar jobs by age (18-44).
   - The standard deviation of log earnings of white-collar jobs by age (18-44).
3. The mean value of personality traits by age, education level and occupation (50 moments)
   - Mean values of "big five" (openness to experience, conscientiousness, extraversion, agreeableness, emotional stability) by five-year age groups.[25]
   - Mean values of "big five" (openness to experience, conscientiousness, extraversion, agreeableness, emotional stability) by low education group (educational years ≤ 12) and high education group (educational years > 12). [26]

[22] 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.

[23] 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.

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

[25] The four-year age groups are 15-19, 20-24, 25-29, 30-34, 35-39, 40-44.

[26] The moments conditioning on educational years are constructed based on those individuals who are beyond age 30.

- Mean values of “big five” (openness to experience, conscientiousness, extraversion, agreeableness, emotional stability) by blue collar workers and white collar workers.

4. Moments that equate the distribution of initial personal traits for different age groups (20 moments):

   - The difference (mean and std deviation) of “big five” (openness to experience, conscientiousness, extraversion, agreeableness, emotional stability) between young age group (15-24) and middle age groups (25-34,35-44).

As previously noted, for older cohorts we only observe personality traits at later ages and have to impute the initial values. The last 20 moments ensure that the imputed initial distributions for older cohorts match the observed initial distributions for younger cohorts.[27]

7 Estimates

7.1 Parameter Values

Tables 8-10 show the model parameter estimates along with standard errors. Table 8 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 4.37 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 20.04 percent, and one-year of blue-collar experience increases blue-collar wages by 29.42 percent. White-collar experience has a significant return in the blue-collar sector and blue-collar experience is also 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. We normalize the non-pecuniary utility from a white-collar job to 0. The non-pecuniary blue collar job premium is AU$32,188 for individuals who are not college graduates but only AU$2,911 (=32,188-29,277) for college graduates.

For the schooling option, we estimate a utility of AU$33,100 per year if an individual stays in school until age 18; this relatively high utility is needed for the model to be able to capture the drop-off in schooling after high school graduation. We find a net lump-sum cost of college education of AU$117,199 and a one-time cost of graduate school of AU$146,500.[28] This cost includes both tuition and living expenditures as well as

[27]The initial conditions of earlier and later cohorts may still differ, though, because of differences in family background. The model also allows for cohort effects on the sector-specific rewards.

[28]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.

potential psychological costs. Also, higher cognitive ability increases the return from school attendance.

With regard to the home staying option, the flow utility is specified as quadratic in age, but we do not find much evidence of variation with age. The utility of staying home increases from AU$0.39 at age 15 to AU$2.327 at age 65. Lastly, we estimate a discount rate parameter, β, equal to 0.9060 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 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 for type I (AU$78051) is slightly higher than that of type IV (AU$69813), but much higher than for types II (AU$40436) and III (AU$11,289). For the option of staying home, the rewards associated with types I-IV are AU$43,452, AU$40,062, AU$32969 and AU$28,318.

Table 9 shows the parameter estimates from the estimation of the initial type probability functions (which are assumed to be multinomial logistic). The initial type probabilities depend on age 15 personality traits as well as family background (as measured by parental education and whether the individual grew up with both parents).

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 or type III. A person with high conscientiousness is more likely to be type I or III and less likely to be types II or IV. High agreeableness leads a lower likelihood of being type I. The last two rows of table 9 show the malleability of types over time and how types become more persistent with age.

Table 10 shows the estimates of the probability that personality traits change, which is assumed to potentially depend on education and age. One additional year of education at age 15 increases personality trait scores. It increases the level of openness to experience by 0.11 (std. dev. units), conscientiousness by 0.07, extraversion by 0.02, agreeableness by 0.08 and emotional stability by 0.05. [29] 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. Another pattern is that extraversion decreases with age.

Figure 4 shows the probability of changing type. It starts at around 0.75 at age 15 then diminishes to almost 0 around age 28. In other words, our estimation results show that the types become relatively fixed in the late 20s.

[29]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.

7.2 Model Fit

Figure 5 compares model simulations with the data. The estimated moments pertain to the proportion choosing different sectors over the life cycle (figure 5) and the log wage of white-collar and blue-collar occupations over the life-cycle (figure 5).

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 diminishes somewhat. (3) Except for a small hump shape in the early 20s, the fraction that stays home 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. (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. However, the simulated log earnings for the white collar sector are too high at younger ages (recall that very few people work in that sector at young ages). (6) The simulated standard errors fit the observed average level reasonably well.

Table 11 shows mean values of personality traits by age, education and occupational categories. It compares means derived directly from the data to the means implied by the simulated model. It shows that the model captures fairly well the time trends with age and the differences by education and occupation.

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 ex-ante heterogeneity compared with other initial endowments. 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

Table 12 examines the type distributions within the different sectors. White-collar workers tend to be types I or IV, whereas blue-collar workers tend to be types II and III. Also, individuals attending school are more likely to be types I and IV, possibly because longer periods of schooling are usually required to be a white-collar worker. Home-stayers are predominantly type III.

Figure 7, a radar chart, provides a graphical depiction of the 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 at different ages. With age, the proportions of type II and IV, decrease while the proportions of type I and III increase. The changes are driven primarily by increasing levels of conscientiousness. The estimates in table 10 indicate that the average level of conscientiousness increases over time, both because of increasing levels of education and because of a direct age effect. A higher conscientiousness score increases the probability of being type I or type III.

8.2 Understanding the effect of personality traits on education, earnings and ex-ante life-time utility

Table 13 presents the simulated effects of a one-unit standard deviation increase in initial personality traits and cognitive abilities on earnings, education, occupational category, and ex-ante utility at ages 35-40. Increases in the initial level of openness to experience, conscientiousness, or agreeable generate large increases in log earnings and make it more likely that a person has a white collar occupation. These traits also increase the fraction of type I’s in the population. An increase in conscientiousness and in agreeableness lead to higher levels of education, perhaps because these traits facilitate success in school. An increase in the cognitive score also increases earnings, but it decreases education. This is because an increase in cognitive ability increases the wage offer and makes work options more attractive relative to schooling.[30]

8.3 Testing the hypothesis of type stability

As previously noted, our model allows the unobserved types to evolve in a way that may depend on age and on personality traits. In this section, we test the validity of this assumption by comparing our model with an two alternative “fixed type” models. In the first, we allow the type probabilities to depend on initial personality traits and on family background. In the second, types are drawn from a multinomial distribution where the probabilities do not depend on regressors. We test each of these models against our more benchmark model with time-varying types using a likelihood-ratio (LR) test. As seen in Table 14, the fixed type models are both rejected with a p-value less than 0.01. Later, we will also consider how implied policy effects differ for a fixed-type verses varying-type model.

[30]Cognitive ability was only measured in one wave of the data, so we do not attempt to model the effect of schooling on acquiring cognitive ability.

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

We next use the estimated dynamic discrete choice models, both the variable-type and the fixed-type variants, to evaluate the effects of two education policies, a college tuition subsidy program and a compulsory schooling policy.

9.1 Using the model to simulate the effects of educational policies

In 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 the upfront payment. Some students also receive direct financial help to cover living expenditures through a 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 policy that reduces the cost of attending college by 50%.

Our second policy experiment is motivated by the spatial variation in compulsory schooling requirements 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 minimum age in other areas was between 15-16. [31] In 2010, areas with lower compulsory school attendance ages came up with plans to increase compulsory schooling.[32] As a result, students in all states and territories are now required to stay in school until age 17. (National Report on Schooling in Australia 2011) Inspired by these policies, we consider the imposition of a perfectly enforced national compulsory secondary school rule that mandates individuals to stay in school until at least age 17.[33]

We next use the model to simulate to the effects of the two education policies previously described, considering both mean effects and distributional effects. To understand the importance of allowing for time-varying types, we compare the simulated policy effects for 4215 individuals that we obtain under the baseline model to those obtained under a restricted "fixed type" model. Table 15 shows the effect of the two policies.[34] Specifically, we examine effects on (1) the percentage high school graduates; (2) the percentage

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

[32] 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.

[33] Individuals who are younger than age 18 after the year 2009 in HILDA data should be already subject to the compulsory education policy. However, currently, the policy is not strictly enforced. The school enrollment rates for teenagers ages 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 differ for years prior to 2009. Our baseline model estimation assumes no compulsory schooling law and we simulate the effects of a compulsory schooling law that is strictly enforced.

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

college graduates; (3) the average years of education; (4) the annual earnings for workers; and (5) the expected lifetime utility gain. In each of these 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 high school completion rate (+16pp), whereas the college subsidy has the largest positive impact on the fraction of college graduates (+17pp). Second, these two policies affect different types of individuals. The college subsidy increases the average years of completed education by 0.5-1.1 years for types I, II and IV but not at all for type IIII. In contrast, the compulsory school policy increases years of education by about 0.2-0.6 years for types II and III but has 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$ 3751 and AU$ 2800. The increases observed for types II and III are AU$ 2018 and AU$ -1. When implementing the compulsory schooling policy, types II and III benefit the most. The annual earnings increases of those two types are AU$ 855 and AU$ 1076, whereas the changes for other two types are only AU$ -6 and AU$ 0. High school completion is already so prevalent among types I and IV, so few individuals of those types are affected 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. In terms of utility, types I and IV benefit the most from the college subsidy policy. All types have a negative utility change from the compulsory schooling requirement, as it represents a constraint on their choices at early ages.

Table 16 reports the effects of two policies on personality traits at age 30 (when most have completed their education). The "benchmark" row shows the average trait score of each type. The rows "50% college subsidy" and "compulsory senior secondary school" report the additional change under these two policies. In general, the effects of both policies on traits are positive. Of the two policies, the college tuition subsidy has the greatest effect, increasing openness to experience, conscientiousness and emotional stability. The effects of the compulsory schooling requirement are focussed on individuals of type II and III, particularly in the areas of openness to experience, conscientiousness, and emotional stability.

Table 17 simulates the cost and benefits of the two policies and explores how these policies affect earnings inequality. The tuition subsidy leads to a decrease in inequality as measured by the 50th/10th quantile earnings ratio and the 90th/10th quantile ratios. In the model, the estimated utility is measured in Australian dollars, so we can compare the average utility gain to the average cost. For the tuition subsidy, the cost exceeds the utility gain on average.[35]

[35] There could, however, be social benefits from individuals having education, such as a reduction in crime.

9.2 Understanding the importance of time-varying types

To understand the empirical importance of allowing for time-varying types, we evaluate the same education policies under the restricted "fixed types" model," in which the type probabilities depend only on family background and initial personality traits and do not vary over time. The results are reported in table 18. Compared with table 15, there are two main differences. First, the policy impacts are now more concentrated among certain types of individuals. The college subsidy policy only affects the college graduation decision of type I and type IV, while the compulsory schooling policy essentially only affects the high school completion rate of types II and III. Second, the effects on labor market earnings 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$ 3410 and AU$ 1271. In contrast, the earnings increase drops to AU$ 2146 and AU$232 in the restricted "fixed type" model. The reason for these differences is straightforward. When type is changeable, the education investment has both a direct reward in terms of increasing wage offers and an indirect reward through the chance to become a different type.

9.3 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. We next investigate the heterogeneous effects of the two education 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.[36] We find the personality patterns between individuals from different backgrounds are similar to that 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.

Tables 19 and 20 summarize the effects of both the college subsidy policy and the compulsory senior secondary school policy. The policy effect of the college tuition subsidy is substantial across all SES groups in terms of increasing education and earnings. We also observe an increase in the percentage of white collar workers and a decrease in the percentage blue collar. As seen in 20, the effect on personality traits - increasing openness to experience, conscientiousness and emotional stability - is also substantial across all the SES groups. The compulsory schooling policy has effects across all SES groups on education, earnings and personality traits, although they are smaller in magnitude than for the tuition subsidy.

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

10 Conclusions

This paper develops a dynamic model of schooling and occupational choices that incorporates personality traits. As is common in the discrete choice literature, we introduce unobservable types' to capture agents' heterogeneous comparative advantages in schooling and particular occupational sectors. In line with some recent papers in the literature (Hu et. al. (2015)and Arcidiacono and Miller (2011)), we adopt a specification with time-varying types, where the probability of changing type can depend on age and on personality traits. We perform a test of the assumption that types are fixed, which is rejected. The estimates indicate that types are malleable when agents are young but become stable by age 28. Another finding is that high levels of cognitive skills and high personality trait scores, in all five dimensions, tend to be clustered in a certain type of individual, type I in our analysis. This type also acquires more schooling and tends to work in the white collar sector. Much of the prior economics literature emphasizes the role of cognitive skills in determining lifetime outcomes. Our analysis shows that cognitive skills are important determinants of wage offers but also that having high cognitive skills, on average, goes hand-in-hand with having high non-cognitive skills.[37] This finding suggests that the importance of cognitive skills as a determinant of labor market success may be overstated in studies that ignore non-cognitive attributes.

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 individuals at risk for not finishing high school, represented by types II and III in the model. The college tuition subsidy mainly benefits types I and IV. However, when the data are divided by SES family background, we see that the policies benefit individuals who come from all the different SES categories.

We show that a model with fixed types ignores the indirect reward of education in becoming a better "type", which is empirically important to consider when evaluating the distributional effect of these policies. The simulated policy responses are greater and the effects more evenly distributed in the population in a model that allows types to change.

Our results also indicate that personality traits are an important factor in explaining ex-ante heterogeneity, which, as was demonstrated in Keane and Wolpin (1997), is a major determinant of ex-ante life-time inequality. We find that one of the benefits of attending school is that it changes some personality traits, which, along with increased schooling levels, enhances earnings. One caveat to our findings is that personality endowments in our model are measured as of age 15, and 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 desirable personality traits may be policies that are targeted during early

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

childhood years rather than high school or post-secondary schooling interventions.

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Appendices

.1 Identification of the transition matrix

We provide the sketch of proof how the Markov law of motion $\Pr(d_m(a), s_{-k}(a), k(a)|d_m(a-1), s_{-k}(a-1), k(a-1))$ can be identified based on observations from at least three periods $\{d_m(a), s_{-k}(a), d_m(a-1), s_{-k}(a-1), d_m(a-2)\}$. Following Hu et al. (2015), the law of motion can be factored into the following three components:

$$\begin{aligned} &\Pr(d_m(a), s_{-k}(a), k(a)|d_m(a-1), s_{-k}(a-1), k(a-1)) \\ =& \underbrace{\Pr(d_m(a)|s_{-k}(a), k(a))}_{\text{CCP}} \underbrace{\Pr(k(a)|s_{-k}(a), s_{-k}(a-1), k(a-1))}_{\text{Law of motion for type k}} \underbrace{\Pr(s_{-k}(a)|d_m(a-1), s_k(a-1), k(a-1))}_{\text{Law of motion for } s_{-k}} \end{aligned}$$

To apply the proof in Hu et al. (2015), we make the following assumption:

Assumption 1. ***Limited feedback:*** *(1)*$\Pr(d_m(a)|s_{-k}(a), k(a), s_{-k}(a-1), k(a-1), d_m(a-1)) = \Pr(d_m(a)|s_{-k}(a), k(a))$. *(2)* $\Pr(k(a)|s_{-k}(a), s_{-k}(a-1), k(a-1), d_m(a-1)) = \Pr(k(a)|s_{-k}(a), s_{-k}(a-1), k(a-1))$.

To ensure the existence and uniqueness of the decomposition, we further impose the following three assumptions:

Assumption 2. ***Full rank:*** *for any*$\{s_{-k}(a), d_m(a-1), s_k(a-1)\}$,

$$[\Pr(d_m(a) = i, s_{-k}(a), d_m(a-1)|s_{-k}(a-1), d_m(a-2) = j)]_{i,j}$$

is invertible.

Assumption 3. ***Distinctive types:*** *For any two different types k_1 and k_2 at age a-1,* $\forall k_1, k_2 \in k(a-1)$

$$\Pr(d_m(a-1)|s_{-k}(a), s_{-k}(a-1), k_1(a-1)) \neq \Pr(d_m(a-1)|s_{-k}(a), s_{-k}(a-1), k_2(a-1))$$

Assumption 4. ***First order stochastic dominance:*** $\Pr(d_m(a-1)|s_{-k}(a), s_{-k}(a-1), k(a-1))$ *is stochastically increasing in the sense of first-order stochastic increasing in $k(a-1)$ for fixed $(s_{-k}(a), s_k(a-1))$.*

Theorem 5. *Under assumptions 1,2,3,4, the density function* $\Pr(d_m(a), s_{-k}(a), d_m(a-1), s_{-k}(a-1), d_m(a-2))$ *uniquely determines the conditional probability function* $\Pr(d_m(a)|s_{-k}(a), k(a))$*, the law of motion for k* $\Pr(k(a)|s_{-k}(a), s_{-k}(a-1), k(a-1))$ *and the law of motion for the rest state variables* $\Pr(s_{-k}(a)|d_m(a), s_{-k}(a-1), k(a-1))$.

Proof. Our proof of theorem 5 follows Hu et al. (2015). Although their proof is for the stationary Markov kernel case, we find their theorem still applies to our case where the conditional choice probability is age-dependent. We assume that the discrete values $\{d_m(a-2), d_m(a-1), d_m(a), s_o(a), s_o(a-1)\}$ share the common support $\{1, 2, ..., J\}$, then introduce the following notations of J-dimensional square matrices.

$$
\begin{aligned}
A &= [\Pr(d_m(a) = i, s_{-k}(a), d_m(a-1) | s_{-k}(a-1), d_m(a-2) = j)]_{i,j}\,; \\
B &= [\Pr(d_m(a) = i | s_{-k}(a), s_{-k}(a-1), k(a-1) = k)]_{i,k}\,; \\
C &= [\Pr(k(a-1) = k | s_{-k}(a-1), d_m(a-2) = j)]_{k,j}; \\
D_1 &= diag\{[\Pr(d_m(a-1)) | s_{-k}(a), s_{-k}(a-1), k(a-1) = k]_k\}; \\
D_2 &= diag\{[\Pr(s_{-k}(a) | s_{-k}(a-1), k(a-1) = k)]_k\}; \\
E &= [\Pr(d_m(a) = i, s_{-k}(a) | s_{-k}(a-1), d_m(a-2) = j)]_{i,j}; \\
F &= [\Pr(k(a) = l | s_{-k}(a), s_{-k}(a-1), k(a-1) = k)]_{l,k}; \\
G &= [\Pr(d_m(a) = i | s_{-k}(a), k(a) = l)]_{i,l} \\
H &= [\Pr(s_{-k}(a) | s_{-k}(a-1), k(a-1) = k) \cdot \Pr(k(a-1) = k | s_{-k}(a-1), d_m(a-2))]_{k,j}
\end{aligned}
$$

Among all the above matrices, only matrices A and E are observed. Given the matrix definitions above, the following equation

$$
\begin{aligned}
&\Pr(d_m(a), s_{-k}(a-1), d_m(a-1) | s_{-k}(a-1), d_m(a-2)) = \\
&\sum_{k(a-1)} \Pr(d_m(a) | s_{-k}(a), s_{-k}(a-1), k(a-1)) \Pr(d_m(a-1), s_{-k}(a) | s_{-k}(a-1), k(a-1)) \Pr(k(a-1) | s_{-k}(a-1), d_m(a-2))
\end{aligned} \tag{14}
$$

has a simpler expression

$$A = B \cdot D_1 \cdot D_2 \cdot C$$

Integrating out $d_m(a-1)$ in equation 14 yields

$$
\begin{aligned}
&\Pr(d_m(a), s_{-k}(a) | s_{-k}(a-1), d_m(a-2)) = \\
&\sum_{k(a-1)} \Pr(d_m(a) | s_{-k}(a), s_{-k}(a-1), k(a-1)) \Pr(s_{-k}(a) | s_{-k}(a-1), k(a-1)) \Pr(k(a-1) | s_{-k}(a-1), d_m(a-2))
\end{aligned} \tag{15}
$$

which is equivalent to the following matrix notation equation

$$E = B \cdot D_2 \cdot C$$

Given the assumption that E is invertible (Assumption 2), we can get

$$A \cdot E^{-1} = B \cdot D_1 \cdot B^{-1}$$

Further use the assumption 3, the eigenvalue-eigenvector of $A \cdot E^{-1}$ should be unique[38], thus B is identified as the eigenvector and D_1 is identified as eigenvalues. The assumption 3 also infer that B and D_1 are both invertible, thus we have the identification of H:

$$H \equiv D_2 \cdot C = D_1^{-1} \cdot B^{-1} \cdot A$$

Therefore, D_2 and C are identified separately under Assumption 4. □

Corollary 6. *The age-dependent conditional choice probability* $\Pr(d_m(a)|s_{-k}(a), k(a))$ *and law of motion for* $s_{-k}(a)$ *are identified non-parametrically.*

Given the identification of D_1 and D_2, we can identify

$$\Pr(s_{-k}(a), d_m(a-1)|s_{-k}(a), k(a-1)) = \Pr(d_m(a-1)|s_{-k}(a), s_{-k}(a-1), k(a-1)) \Pr(s_{-k}(a)|s_{-k}(a-1), k(a-1))$$

Them the age-dependent conditional choice probability and law of motion for $s_{-k}(a)$ are two marginal distributions of $\Pr(s_{-k}(a), d_m(a-1)|s_{-k}(a), k(a-1))$:

$$\Pr(s_{-k}(a), d_m(a-1)|s_{-k}(a), k(a-1)) = \underbrace{\Pr(d_m(a-1)|s_{-k}(a), k(a-1))}_{CCP} \underbrace{\Pr(s_{-k}(a)|d_m(a-1), s_{-k}(a-1), k(a-1))}_{\text{law of motion for } s_{-k}}$$

Corollary 7. *The law of motion for types* $\Pr(k(a)|s_{-k}(a), s_{-k}(a-1), k(a-1))$ *is also identified non-parametrically.*

F is the law of motion for k, and G is the conditional choice probability we just identified. Given $B = G \cdot F$, F can be recovered by the equation $F = G^{-1} \cdot B$. The conclusions from corollary 6 and corollary 7 complete the proof.

.2 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

[38]The summation of each column of B should be equal to one. Thus the decomposition is unique up to this normalization constraint

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 the projection of initial personality $\theta_n(15)$ based on the measures on age $a_1 \theta_n(a_1)$:

$$\theta_n(15) = \theta_n(a_1) - (\gamma_{0n} + \gamma_{1n} g(a_1) + \gamma_{2n}(a-15)g(a) + \gamma_{3n}(a-15) + \gamma_{4n}(a-15)^2)$$

   where a_1 is the age when individual's personality trait θ_n is surveyed and $g(a)$ is the accumulative education years at age a_1.

2. Substituting $\theta_n(a_1) = \theta_n^{M1}(a_1) - \zeta_n(a_1)$, where $\zeta_n(a_1)$ is the unobserved measurement error at age a_1 with mean 0. Then

$$\theta_n(15) = \theta_n^{M1}(a_1) - (\gamma_{0n} + \gamma_{1n} g(a_1) + \gamma_{2n}(a-15)g(a) + \gamma_{3n}(a-15) + \gamma_{4n}(a-15)^2) - \zeta_n(a_1)$$

3. Define $\theta_n^{M1}(15) \equiv \theta_n(15) + \zeta_n(a_1)$, its value could be directly calculated by

$$\theta_n^{M1}(15) = \theta_n^{M1}(a_1) - (\gamma_{0n} + \gamma_{1n} g(a_1) + \gamma_{2n}(a-15)g(a) + \gamma_{3n}(a-15) + \gamma_{4n}(a-15)^2)$$

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 0 drawn from an i.i.d distribution. We obtain our measure of the personality trait at age 15 $\theta_n(15)$ as the mean of these three values:

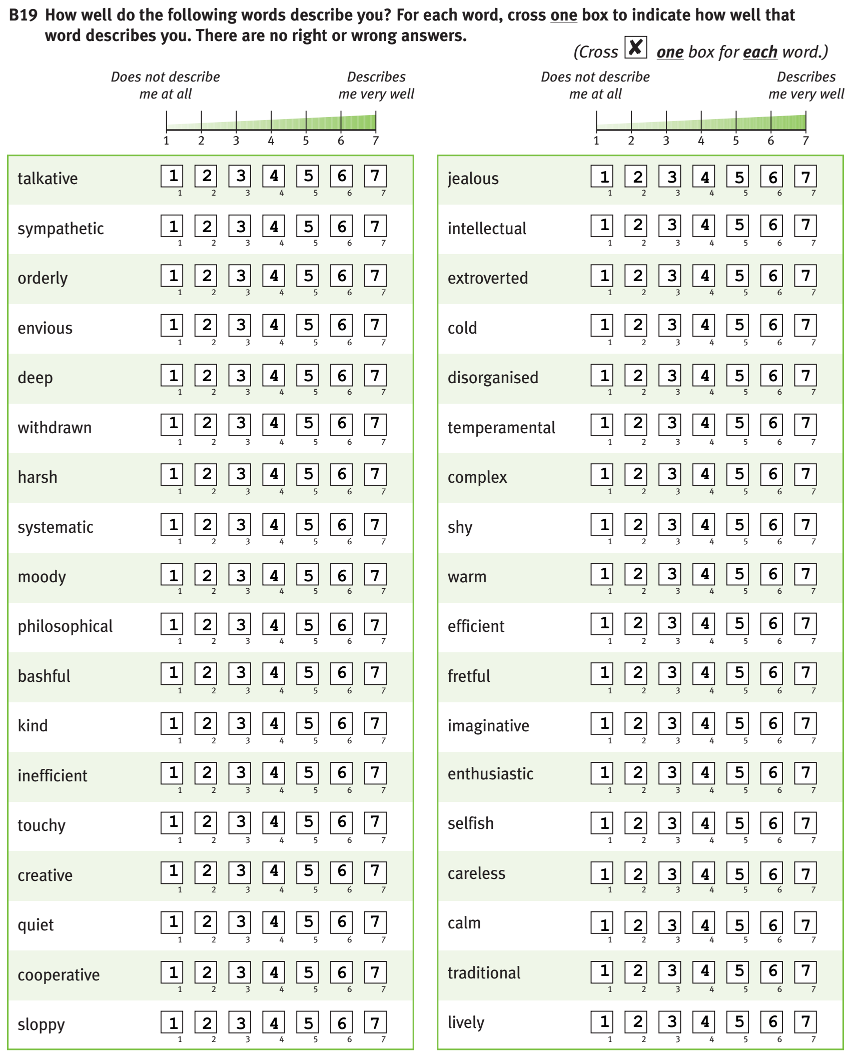
$$\theta_n(15) = \frac{1}{3}(\theta_n^{M1}(15) + \theta_n^{M2}(15) + \theta_n^{M3}(15))$$

Tables

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

Collars	Occupations	Examples
White Collar	Managers	Legislators, senior officials, corporate/general managers
	Professionals	Professionals, physicians, mathematician, engineer and life science
	Technicians and tradespersons	Technicians and associate professionals, physical and engineering scientists, life science and health associate
	Clerical and administrative workers	Service workers and shop workers, personal and protective service workers, models, salespersons
Blue Collar	Community and personal service workers	Office clerks, consumer service clerks
	Sales workers	Sales representative, insurance brokers, checkout operator, models and telemarketers
	Machinery operators and drivers	Industrial spray painters, sewing machinist, motion picture projectionist, crane operator, forklift drivers and train driver
	Labourers	Cleaners, steel fixer, product assembler, packer, slaughter, farm worker, kitchen hand, freight handler and handy persons

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 1 2 3 4 5 6 7 *Describes me very well*

talkative	1	2	3	4	5	6	7	jealous	1	2	3	4	5	6	7
sympathetic	1	2	3	4	5	6	7	intellectual	1	2	3	4	5	6	7
orderly	1	2	3	4	5	6	7	extroverted	1	2	3	4	5	6	7
envious	1	2	3	4	5	6	7	cold	1	2	3	4	5	6	7
deep	1	2	3	4	5	6	7	disorganised	1	2	3	4	5	6	7
withdrawn	1	2	3	4	5	6	7	temperamental	1	2	3	4	5	6	7
harsh	1	2	3	4	5	6	7	complex	1	2	3	4	5	6	7
systematic	1	2	3	4	5	6	7	shy	1	2	3	4	5	6	7
moody	1	2	3	4	5	6	7	warm	1	2	3	4	5	6	7
philosophical	1	2	3	4	5	6	7	efficient	1	2	3	4	5	6	7
bashful	1	2	3	4	5	6	7	fretful	1	2	3	4	5	6	7
kind	1	2	3	4	5	6	7	imaginative	1	2	3	4	5	6	7
inefficient	1	2	3	4	5	6	7	enthusiastic	1	2	3	4	5	6	7
touchy	1	2	3	4	5	6	7	selfish	1	2	3	4	5	6	7
creative	1	2	3	4	5	6	7	careless	1	2	3	4	5	6	7
quiet	1	2	3	4	5	6	7	calm	1	2	3	4	5	6	7
cooperative	1	2	3	4	5	6	7	traditional	1	2	3	4	5	6	7
sloppy	1	2	3	4	5	6	7	lively	1	2	3	4	5	6	7

Table 3: Sample summary statistics

Variable	Proportions(%)	Variable	Proportions(%)
State		*Background info when you were 14*	
New South Wales	31.02	***Father Education***	
Victoria	25.46	College	64.52
Queensland	20.42	Not College	35.48
South Australia	8.83	***Mother Education***	
Western Australia	8.83	College	49.05
Tasmania	2.83	Not College	50.95
Northern Territory	0.55	***Father Working***	
Australian Capital Territory	2.08	Employed	95.81
Year (Cohort)		Not Employed	4.19
1961-1969	20.01	***Father Occupation***	
1970-1979	28.83	White Collar	72.32
1980-1989	27.13	Blue Collar	27.68
1990-1998	24.03	***Mother Working***	
Ever had siblings		Employed	63.70
Had siblings	95.71	Not Employed	36.30
No siblings	4.29	***Mother Occupation***	
Sibling numbers		Not Asked	16.43
Not Asked	4.36	White Collar	52.86
1	29.41	Blue Collar	30.71
2	32.48	***Family Intactness***	
3	17.01	Both parents	80.3
4	8.79	Father and step	1.3
5 or more	7.95	Mother and step	5.01
Eldest Sibling		Father only	3.03
Not Asked	4.29	Mother only	8.76
Oldest	34.9	Other	1.6
Not Oldest	60.8		
Total Individuals		2,934	

Note: this table shows the summary statistics for males whose ages are between 15 and 44. The family background information (parental education, employment, occupations and family intactness) are the situations when individuals were at age 14. Data source: HILDA data, 2001-2013.

Table 4: Average personality traits by education level

Education Level	Openness to experience	Conscientiousness	Agreeableness	Extroversion	Emotional stability
Secondary school or lower	4.243	4.824	5.070	4.447	5.026
	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)
College dropouts	4.357	4.883	5.122	4.350	5.012
	(0.022)	(0.023)	(0.019)	(0.023)	(0.022)
College graduates	4.577	5.028	5.160	4.293	5.113
	(0.012)	(0.012)	(0.010)	(0.013)	(0.012)

Note: this table shows the mean and standard error (in parentheses) of the "big-five" personality traits by education groups (secondary school or lower, college dropouts, college graduates). The sample is HILDA, waves 5, 9 and 13. Each trait has a value ranging from 1 to 7.

Table 5: Average personality traits by occupation category

Occupation	Openness to experience	Conscientiousness	Agreeableness	Extroversion	Emotional stability
White-collar	4.452	5.035	5.159	4.381	5.091
	(0.010)	(0.010)	(0.009)	(0.011)	(0.010)
Blue-collar	4.153	4.887	5.088	4.382	5.015
	(0.011)	(0.011)	(0.010)	(0.010)	(0.011)

Note: this table shows the mean and standard error (in parentheses) of the "big five" personality traits by occupation group (white collar and blue collar). The sample is HILDA, waves 5, 9 and 13. Each personality trait has a value range between 1 to 7.

Table 6: The effect of changes in education/occupation on personality traits

	(1) Opn	(2) Cos	(3) Agr	(4) Stb	(5) Ext
Education (β_1)	0.150*	-0.0489	0.0943	-0.147*	-0.0553
	(0.0587)	(0.0592)	(0.0619)	(0.0642)	(0.0509)
$Age * Edu/100$ (β_2)	-0.493*	0.218	-0.211	0.609*	0.189
	(0.228)	(0.230)	(0.241)	(0.250)	(0.198)
Age (β_3)	0.046	0.112***	0.0482	-0.00726	0.0193
	(0.0322)	(0.0325)	(0.0340)	(0.0352)	(0.0279)
$Age^2/100$ (β_4)	-0.0694	-0.152**	-0.0639	0.0226	-0.0687
	(0.0566)	(0.0572)	(0.0598)	(0.0619)	(0.0491)
White Collar (β_5)	-0.103	0.03	-0.0897	-0.068	-3.69e^{-4}
	(0.0622)	(0.0628)	(0.0657)	(0.0680)	(0.0540)
Blue Collar (β_6)	-0.0267	0.00946	-0.0592	0.0100	0.0122
	(0.0632)	(0.0638)	(0.0667)	(0.0691)	(0.0549)
R^2	0.828	0.823	0.762	0.800	0.866
Observations	2800	2800	2800	2800	2800

Notes: This table reports estimates from fixed-effect panel regressions of “big five” personality traits on the indicated variables. Standard errors are reported in parentheses. Significance levels: $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table 7: How personality traits and cognitive ability relate to log wages

	Log earnings		
	(1)	(2)	(3)
Education	0.116***	0.110***	0.133***
	(0.003)	(0.003)	(0.003)
Potential experience	0.149***	0.148***	0.172***
	(0.004)	(0.004)	(0.005)
Potential experience squared /100	-0.396***	-0.396***	-0.377***
	(0.013)	(0.013)	(0.014)
Openness		-0.054***	-0.056***
		(0.006)	(0.006)
Conscientiousness		0.078***	0.083***
		(0.006)	(0.006)
Emotional stability		-0.015*	-0.011
		(0.006)	(0.006)
Agreeableness		-0.026***	-0.030***
		(0.007)	(0.007)
Extraversion		0.031***	0.028***
		(0.006)	(0.006)
Cognitive		0.077***	0.073***
		(0.009)	(0.009)
Family Characteristics	No	No	Yes
Observations	16408	16408	16408
R Square	0.303	0.318	0.351

Standard errors are reported in parentheses.

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

Notes: Specifications (1) - (3) report the estimates from the OLS regressions of log earnings on education, potential experience, personality traits, cognitive ability and family background ccontrol variables. Standard errors are reported in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Model parameter estimates: reward functions

	1. *White-Collar*		**2. *Blue-Collar***		***3. Schooling***		
	Parameters	S.D.	Parameters	S.D.		Parameters	S.D.
Schooling	0.0437		0.0399		Tuition cost: college	11.7199	
White-Collar experience	0.0385		0.0224		Additional cost:graduate school	14.6500	
Blue-Collar experience	0.0115		0.0147		Additional utility before age 19	3.3100	
"Own" experience squared/100	-0.0397		-0.0194		Cognitive ability	0.2174	
"Own" experience×edu	0.0087		0.0278		**Constant:**		
"Own" experience≤2	0.2004		0.2942		Type I	7.8051	
Cognitive ability	0.1100		0.2400		Type II	4.0436	
Standard Error	0.4808		0.4334		Type III	1.1289	
Constant:					Type IV	6.9813	
Type I	10.356		9.6359		**Cohort (Omitted cat:60-69)**		
Type II	10.236		10.017		70-79	0.3299	
Type III	9.6797		9.1762		80-89	2.1839	
Type IV	9.829		9.0067		90-99	2.0711	
State (Omitted cat:NSW)							
VIC	-0.0836		-0.0893		***4. Home-staying***		
QLD	-0.1353		-0.7000		Age	0.0228	
SA	-0.2999		0.4828		Age squared/100	0.0200	
WA	0.0332		0.0039		**Constant:**		
TAS	-0.2596		-0.1471		Type I	4.3452	
NT	-0.0153		-0.2067		Type II	4.0062	
ACT	0.2718		-0.033		Type III	3.2769	
Cohort (Omitted cat:60-69)					Type IV	2.8318	
70-79	0.0957		0.2192				
80-89	-0.0696		0.0936				
90-99	-0.0999		-0.5408				
Non-pecuniary Values					**Other Primitive Parameters**		
Constant	-		3.2188		Preference Shock	0.9195	
College Premium	-		-2.9277		Discount Factor	0.9060	

Note: Data source: HILDA, 2001-2013. The estimates are based on 2934 males whose personality traits are measured at least one time between ages 15-44. The unit for the non-pecuniary, school and home-staying columns is 10,000AU$.

Table 9: Estimated coefficients on type probabilities

Types	I(baseline)	II	III	IV
Constant term	-	-1.10	-0.30	-0.50
Openness to Experience	-	-0.80	-0.70	0.22
Conscientiousness	-	-0.50	-0.29	-0.52
Extraversion	-	0.22	0.10	-0.47
Agreeableness	-	-0.50	-0.51	-0.48
Emotional Stability	-	-0.11	-0.10	-0.12
Parental Education (Omitted cat: no college)				
One college	-0.250	0.006	-0.081	0.025
Two colleges	0.130	0.1785	-0.110	0.000
Family Intactness Dummy (Omitted cat: intact family)				
Living with at most one parent at age 14	0.075	0.070	0.140	-0.035
Type Persistence	Time shift term		$Age - 15$	$\frac{(Age-15)^2}{100}$
Values	0.31		0.22	1.20

Note: Sample period: 2001-2013. Data source: the Household Income and Labour Dynamics in Australia. The estimates are based on 2934 males whose personality traits are measured at least one time between 15-44.

Table 10: Estimated model coefficients for personality trait transitions

Traits	Edu	$Edu * (Age - 15)/100$	$Age - 15$	$(Age - 15)^2/100$
Openness to Experience	0.1096	-0.3715	0.0078	0.0014
Conscientiousness	0.0716	-0.3045	0.0486	-0.0737
Extraversion	0.0248	-0.1442	-0.0166	0.0143
Agreeableness	0.0785	-0.6331	0.0333	-0.0253
Emotional Stability	0.0516	-0.1444	-0.0237	0.0793

Note: Data source: HILDA, 2001-2013. The estimates are based on 2934 males whose personality traits are measured at least one time between 15-44.

Table 11: The comparison of mean values between real data and model simulations (conditioning on age groups, educational groups and occupational groups)

	Openness to experience		Conscientiousness		Extraversion		Agreeableness		Emotional Stability	
	Data	Sim	Data	Sim	Data	Sim	Data	Sim	Data	Sim
Age groups										
15-19	4.308	4.251	4.532	4.521	4.613	4.613	4.994	4.979	5.083	5.094
20-24	4.377	4.451	4.736	4.789	4.569	4.583	5.085	5.094	5.012	5.055
25-29	4.416	4.427	4.957	4.936	4.411	4.393	5.119	5.115	5.048	5.029
30-34	4.376	4.385	4.956	4.966	4.348	4.360	5.147	5.202	5.039	5.027
35-39	4.328	4.316	5.028	5.034	4.304	4.310	5.149	5.181	5.087	5.073
40-44	4.323	4.306	5.044	5.027	4.204	4.204	5.101	5.118	5.033	5.020
Educational groups										
$year \leq 12$	4.170	4.017	4.992	4.923	4.302	4.325	5.092	5.088	5.024	5.045
$year > 12$	4.552	4.603	5.040	5.093	4.229	4.232	5.176	5.222	5.088	5.031
Occupational groups										
Blue Collar	4.154	4.040	4.887	4.842	4.382	4.399	5.089	5.017	5.014	5.053
White Collar	4.452	4.602	5.035	5.039	4.381	4.312	5.159	5.234	5.090	5.035

Note: This table compares the mean values between real data and model simulations (conditioning on age groups, educational groups and occupational groups). Age groups are divided by five-year ranges: 15-19, 20-24, 25-29, 30-34, 35-39 and 40-44. Educational groups are high education (year>12) and low education (year≤12). And the occupational groups are blue-collar workers and white-collar workers. Data source: HILDA 2005, 2009 and 2013. Males whose personality traits are measured at least one time between 15-44.

Table 12: Simulated type percentages for different sector choices

Occupation		Type I	Type II	Type III	Type IV
White-collar		47.31%	12.83%	9.54%	30.32%
Blue-collar		7.50%	27.87%	53.04%	11.60%
Schooling		37.41%	13.65%	13.74%	35.20%
Home staying		3.48%	5.03%	73.64%	17.85%
Total	Number	25775	15083	26070	21092
	Fraction(%)	29.28%	17.14%	29.62%	23.96%

Table 13: Estimated effects of one-unit standard deviation increase in personality traits and cognitive abilities on (log) annual earning, occupational choices, education years, ex-ante expected utility and initial type distributions

	(Log) Annual Earning	White Collar Occupation	Blue Collar Occupation	Education Years	Ex-ante utility	Initial types at age 15 I	II	III	IV
Baseline	11.181	0.599	0.312	4.534	865,650	0.252	0.192	0.320	0.236
Opn (+1 SD)	0.055	0.099	-0.084	0.485	23,994	0.049	-0.064	-0.107	0.122
Cos (+1 SD)	0.045	0.021	-0.016	0.047	14,646	0.064	-0.026	0.003	-0.041
Ext (+1 SD)	0.007	-0.037	0.033	-0.221	1,135	0.004	0.046	0.024	-0.075
Agr (+1 SD)	0.058	0.052	-0.040	0.181	23,724	0.061	-0.005	-0.036	-0.019
Stb (+1 SD)	0.015	0.010	-0.008	0.017	5,088	0.016	-0.002	-0.004	-0.010
Cog (+1 SD)	0.087	0.010	0.019	-0.085	45,130	0.000	0.000	0.000	0.000

Note: The expected ex-ante utility is an Australian dollar equivalent measure at age 15. The first row displays the simulated levels under baseline model. Rows (2)-(6) display the deviation from the baseline levels from an increase of one standard deviation unit in personality traits and cognitive ability.

Table 14: Tests for model specification

	Baseline model	Types are fixed and determined by initial personality traits	Types are fixed and unobserved
Null Hypothesis		H_0: $P_a = 0$	H_0 :$P_a = 0, \gamma_{4kn} = 0$
Distance measure	3851.619	4030.832	3994.703
LR test		179.213	143.213
The number of restrictions		3	18
$\chi^2(0.01)$ criteria		11.34	34.80

Note: The likelihood ratio is based on the moments related to life-time sector choices and wage profiles.

Table 15: The effect of educational policies on schooling and labor market outcomes, by type

Model	Type I	Type II	Type III	Type IV	Total
	Percentage Finishing High school (%)				
Benchmark	99%	86%	78%	99%	90%
50% college subsidy	0%	1%	2%	0%	1%
Compulsory schooling	1%	14%	22%	1%	10%
	Percentage College Graduates				
Benchmark	44%	25%	24%	49%	35%
50% college subsidy	27%	23%	17%	24%	22%
Compulsory schooling	0%	1%	2%	0%	1%
	Years of Education				
Benchmark	14.12	13.08	12.82	14.25	13.53
50% college subsidy	0.88	0.79	0.58	0.79	0.74
Compulsory schooling	0.01	0.27	0.47	0.02	0.21
	Annual Earnings (for workers, unit: AU$)				
Benchmark	97,310	78,480	69,117	83,236	81,650
50% college subsidy	4,041.3	3,223.6	2,736.8	3,745.3	3,410
Compulsory schooling	69.23	1,632.5	3,117.4	137.49	1,270.8
	Fraction Blue Collar (%)				
Benchmark	20%	38%	41%	21%	30%
50% college subsidy	-3%	-3%	-2%	-4%	-3%
Compulsory schooling	0%	-1%	-2%	0%	-1%
	Fraction White Collar (%)				
Benchmark	75%	55%	46%	72%	61%
50% college subsidy	3%	3%	2%	4%	3%
Compulsory schooling	0%	2%	3%	0%	1%
	Utility Change(Unit: AU$10,000)				
Benchmark	89.71	84.52	84.68	87.43	86.57
50% college subsidy	1.77	1.29	1.31	1.82	1.54
Compulsory schooling	-0.76	-0.94	-0.96	-0.78	-0.87

Note: The rows labeled “50% college subsidy” and “compulsory senior secondary school” show deviations from baseline values under two separate policy experiments. The annual earnings, the fraction blue collar and the fraction white collar are averages earning for workers age 35 to 40.

Table 16: The effect of educational policies on personality traits, by type

Model	Type I	Type II	Type III	Type IV	Total
	Openness to Experience (at age 30)				
Benchmark	4.794	4.034	4.074	4.802	4.419
50% college subsidy	0.051	0.042	0.035	0.049	0.044
Compulsory schooling	0.001	0.022	0.038	0.002	0.017
	Conscientiousness (at age 30)				
Benchmark	5.288	4.809	4.885	4.789	4.949
50% college subsidy	0.026	0.021	0.017	0.025	0.022
Compulsory schooling	0.001	0.011	0.019	0.001	0.009
	Extraversion (at age 30)				
Benchmark	4.609	4.566	4.462	4.043	4.420
50% college subsidy	0.004	0.003	0.003	0.004	0.003
Compulsory schooling	0.000	0.002	0.003	0.000	0.001
	Agreeableness (at age 30)				
Benchmark	5.500	4.973	5.006	5.141	5.156
50% college subsidy	-0.009	-0.007	-0.006	-0.009	-0.008
Compulsory schooling	0.000	-0.004	-0.007	0.000	-0.003
	Emotional Stability (at age 30)				
Benchmark	5.084	5.044	5.048	4.813	5.001
50% college subsidy	0.028	0.023	0.019	0.027	0.024
Compulsory schooling	0.001	0.012	0.021	0.001	0.009

Note: The rows labeled "50% college subsidy" and "compulsory schooling" show the deviations from baseline values under two separate policy experiments. The calculation is based on the simulated values of personality traits at age of 30.

Table 17: Cost-benefit analysis of the two educational policies

	Baseline case (no policy)	50% college subsidy	Compulsory senior secondary school
Earning inequality (for workers) at age 40			
50/10 earnings ratio	3.04	2.88	3.00
90/10 earnings ratio	7.06	6.69	6.92
Expected utility (Unit: AU$ 10000)	86.57	88.11	85.70
Utility changes (Unit: AU)	-	1.54	-0.87
Government expenditure (Unit: AU)	0	2.58	0
Net policy cost (Unit: AU)	0	-1.04	-0.87

Note: Inequality is measured by the 90/10 and 50/10 percentile earnings ratios. The row "Expected utility" reports the expected life-time utility at age 15. The extra gain (loss) under the two policies are reported in the next row "Utility changes". The row "government expenditure" reports the average subsidy the government needs to pay for each individual. The row "Net policy cost" shows the utility changes minus the government expenditures The unit of last four rows is AU$ 10000.

Table 18: The effects of educational policies under the restricted model with fixed types

Model simulation	Type I	Type II	Type III	Type IV	Total
	Percentage Finishing High school				
Benchmark	100%	87%	59%	100%	84%
50% college subsidy	0%	0%	0%	0%	0%
Compulsory senior secondary school	0%	13%	41%	0%	16%
	Percentage College Graduates				
Benchmark	53%	0%	0%	75%	31%
50% college subsidy	36%	21%	0%	18%	17%
Compulsory senior secondary school	0%	0%	0%	0%	0%
	Years of Education				
Benchmark	14.55	12.14	11.38	15.26	13.24
50% college subsidy	1.10	0.66	0.00	0.57	0.54
Compulsory senior secondary school	0.00	0.21	0.65	0.00	0.25
	Annual Earnings (for workers, unit: AU$)				
Benchmark	123,780	84,770	29,981	68,881	77,077
50% college subsidy	3,751.3	2,017.9	-0.79	2,799.7	2,146.3
Compulsory senior secondary school	-5.78	854.9	1076	0.43	232.36
	Fraction of Blue Collar Workers (%)				
Benchmark	7%	62%	68%	10%	38%
50% college subsidy	0%	0%	0%	-3%	-1%
Compulsory senior secondary school	0%	0%	1%	0%	0%
	Fraction of White Collar Workers (%)				
Benchmark	92%	37%	7%	84%	52%
50% college subsidy	0%	0%	0%	4%	1%
Compulsory senior secondary school	0%	0%	0%	0%	0%
	Utility Change (Unit: AU$10,000)				
Benchmark	88.95	84.09	84.17	86.76	85.97
50% college subsidy	1.66	1.23	1.26	1.74	1.47
Compulsory senior secondary school	-0.47	-0.61	-0.62	-0.44	-0.54

Note: The rows labeled "50% college subsidy" and "compulsory senior secondary school" show the deviations from baseline values under the two separate policy experiments.

Table 19: The effect of educational policies on labor market outcomes by SES background

Model simulation	Socio Economic Status (SES)			
	I	II	III	Total
	Percentage Finishing High school			
Benchmark	86%	88%	93%	90%
50% college subsidy	0%	1%	1%	1%
Compulsory senior secondary school	14%	12%	7%	10%
	Percentage College Graduates			
Benchmark	26%	31%	44%	35%
50% college subsidy	24%	22%	21%	22%
Compulsory senior secondary school	0%	1%	1%	1%
	Education Years			
Benchmark	13.16	13.35	13.95	13.53
50% college subsidy	0.82	0.76	0.68	0.74
Compulsory senior secondary school	0.25	0.25	0.15	0.21
	Annual Earnings (for workers)			
Benchmark	77,360	77,965	87,747	81,650
50% college subsidy	3,504.8	3,422.8	3,372.1	3,410.0
Compulsory senior secondary school	1,326.8	1,387.7	1,148.8	1,270.8
	Fraction of Blue Collar (%)			
Benchmark	35%	34%	24%	30%
50% college subsidy	-3%	-3%	-3%	-3%
Compulsory senior secondary school	-1%	-1%	-1%	-1%
	Fraction of White Collar (%)			
Benchmark	55%	57%	69%	61%
50% college subsidy	4%	3%	3%	3%
Compulsory senior secondary school	2%	1%	1%	1%
	Utility Gain(Unit: AU$10,000)			
Benchmark	84.05	85.12	89.56	86.57
50% college subsidy	1.32	1.41	1.81	1.54
Compulsory senior secondary school	-1.00	-0.96	-0.68	-0.87

Note: The rows labeled "50% college subsidy" and "compulsory senior secondary school" show the deviations from baseline values under the two separate policy experiments.

Table 20: The effect of educational policies on personality traits by SES background

Personality Traits at age 30	Socio Economic Status (SES)			
Model simulation	I	II	III	Total
	Openness to Experience			
Benchmark	4.250	4.373	4.572	4.419
50% college subsidy	0.049	0.045	0.039	0.044
Compulsory senior secondary school	0.021	0.019	0.013	0.017
	Conscientiousness			
Benchmark	4.930	4.938	4.972	4.949
50% college subsidy	0.025	0.023	0.019	0.022
Compulsory senior secondary school	0.010	0.010	0.006	0.009
	Extraversion			
Benchmark	4.349	4.420	4.467	4.420
50% college subsidy	0.004	0.004	0.003	0.003
Compulsory senior secondary school	0.002	0.002	0.001	0.001
	Agreeableness			
Benchmark	5.096	5.130	5.219	5.156
50% college subsidy	-0.009	-0.008	-0.007	-0.008
Compulsory senior secondary school	-0.004	-0.003	-0.002	-0.003
	Emotional Stability			
Benchmark	4.956	5.009	5.021	5.001
50% college subsidy	0.027	0.025	0.021	0.024
Compulsory senior secondary school	0.011	0.011	0.007	0.009

Note: The rows labeled "50% college subsidy" and "compulsory senior secondary school" show the deviations from baseline values under the two policy experiments. The calculation is based on model simulations of personality traits at age of 30.

Figure Captions

Figure 1. Work status and college attendance by age(% of the same age cohort)

Figure 2. Average annual earnings by Occupation over the life-cycle

Figure 3. The scores of “big five” personality traits over time

Figure 4. The probability of changing type by age

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

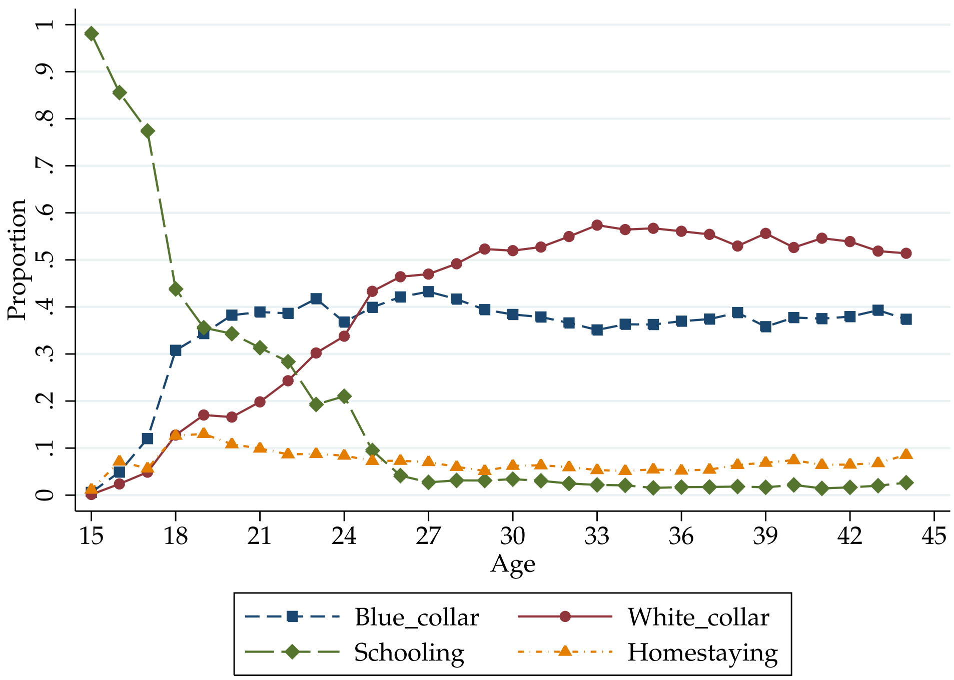
Figure 6. The comparison of personality traits between measured distributions and imputed distributions

Figure 7. Average personality traits and cognitive ability by type

Figure 8. How the type distribution changes with age

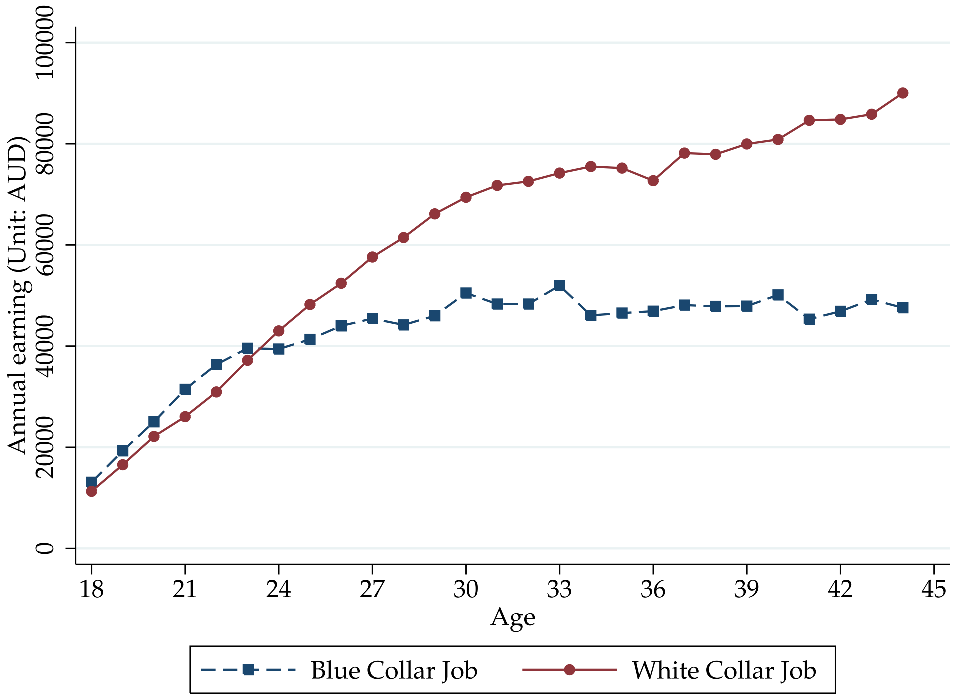
Figures

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



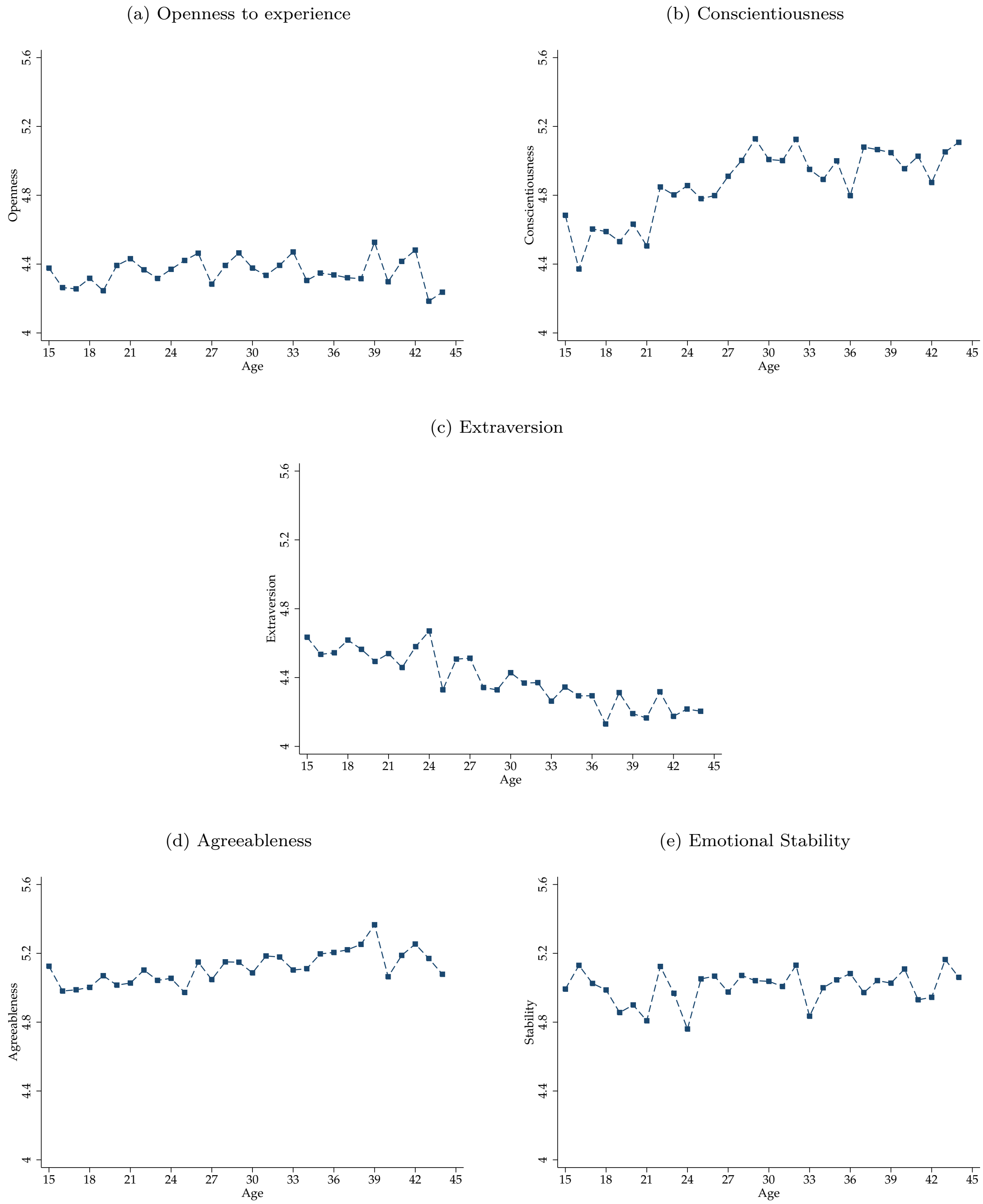
Note: this figure shows the fractions of four choices (schooling, blue collar, white collar, home staying) over the age cohort (15-44). Data source: HILDA data, 2001-2013.

Figure 2: Average annual earnings by Occupation over the life-cycle



Note: this figure shows the average annul earnings of blue collar workers and white collar workers within each age cohort (18-44). Data source: HILDA data, 2001-2013.

Figure 3: The scores of “big five” personality traits over time



Notes: This figure shows the change of “big five” personality traits over time. The measures are based on males between age 15 to 45 who reports their personality traits in wave 13, HILDA.

Figure 4: The probability of changing type by age

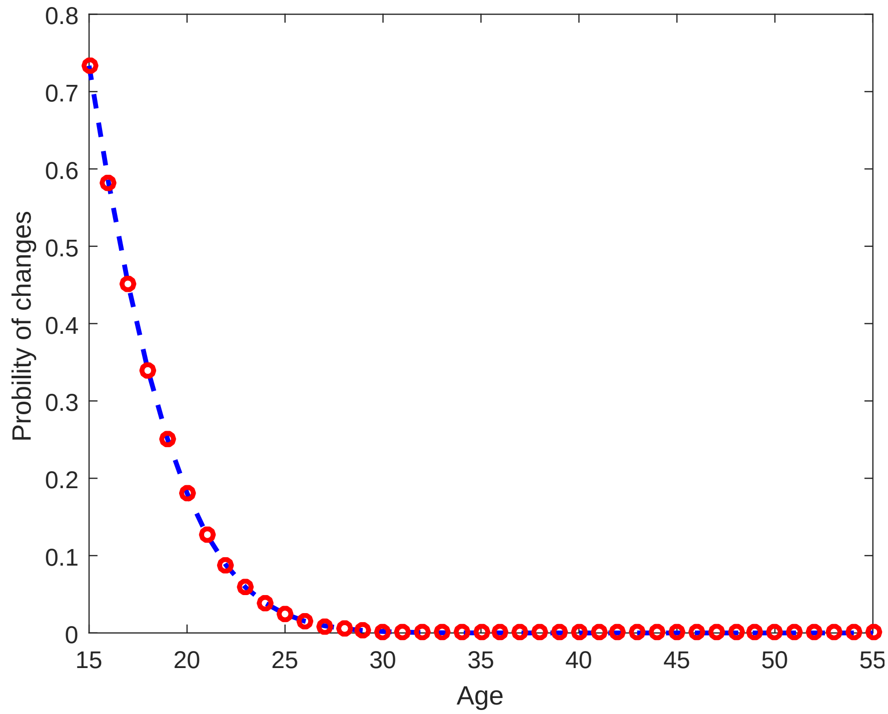
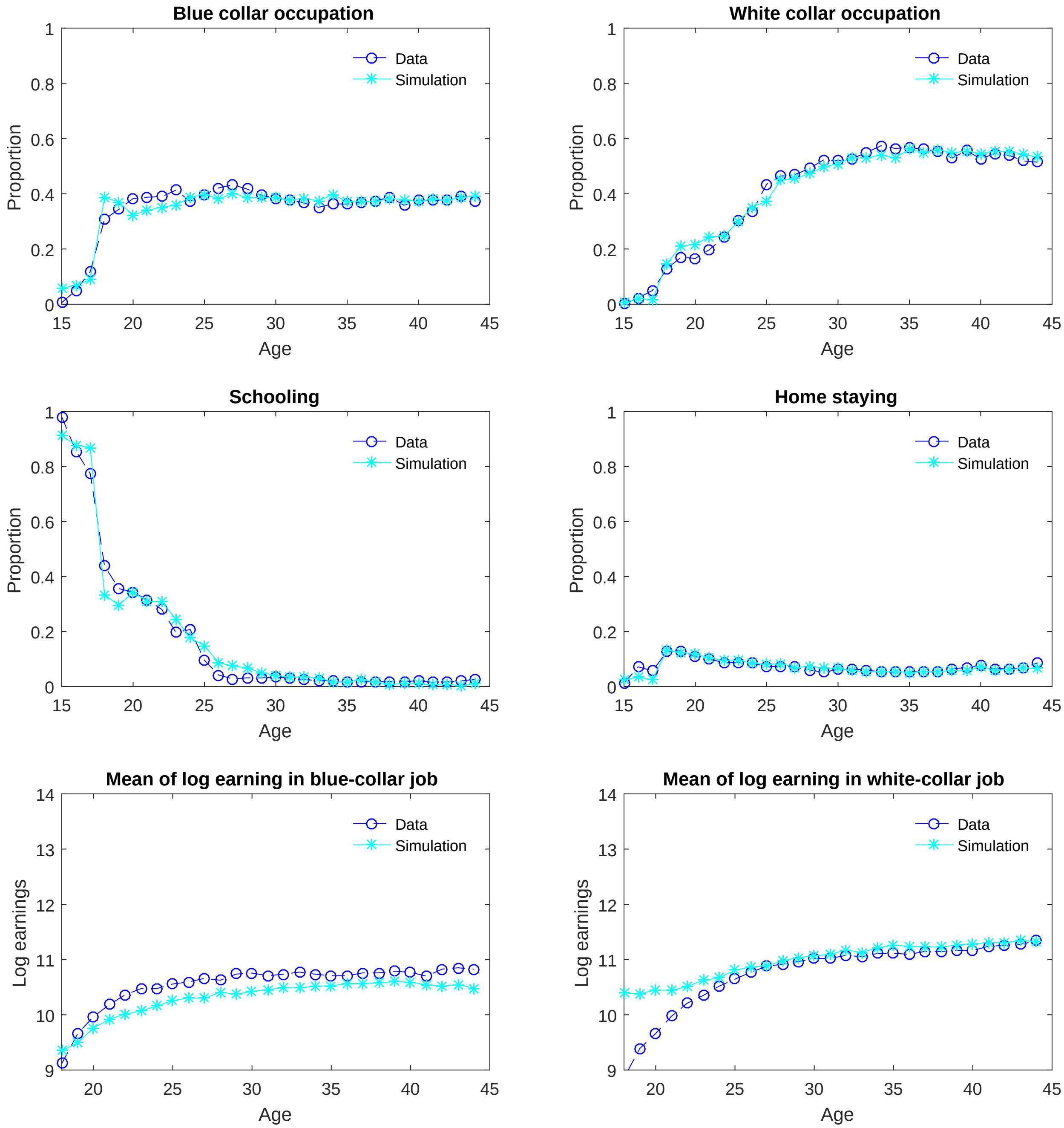


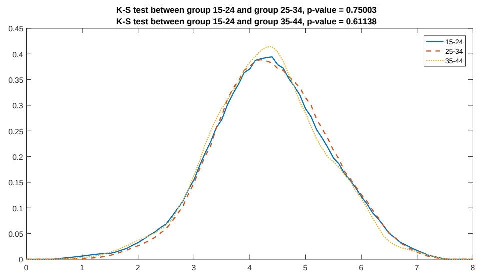
Figure 5: The comparison of choice distribution and earning profile between real data and model simulations



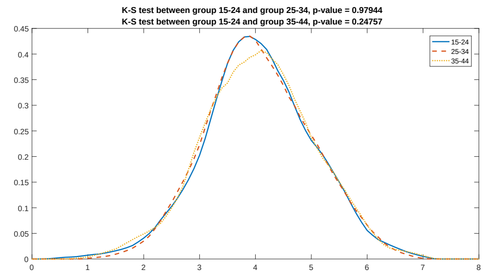
Note: this figure display the fraction of each choices and log earnings over life-time. Data in dashed lines with cycle makers, simulations in dashed lines with star markers.

Figure 6: The comparison of personality traits between measured distributions and imputed distributions

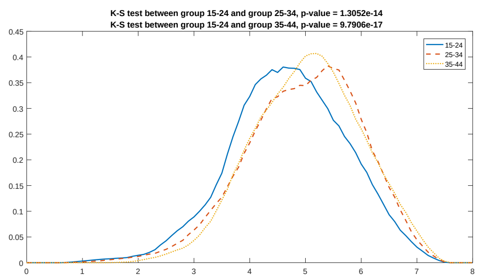
(a) Measured openness to experience



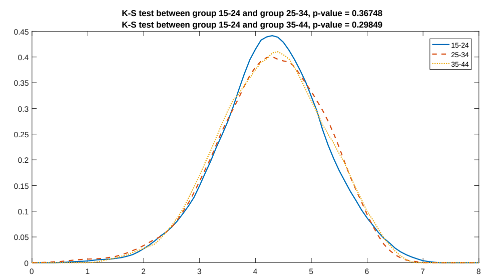
(b) Imputed openness to experience



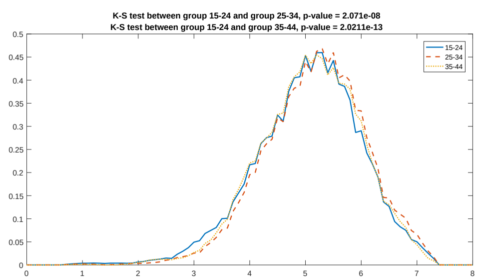
(c) Measured conscientiousness



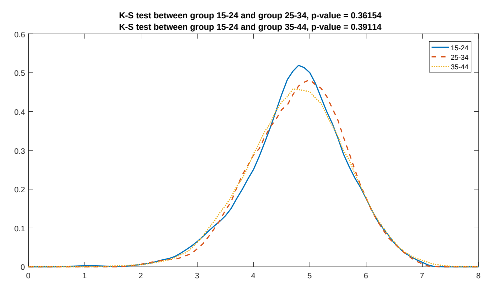
(d) Imputed conscientiousness



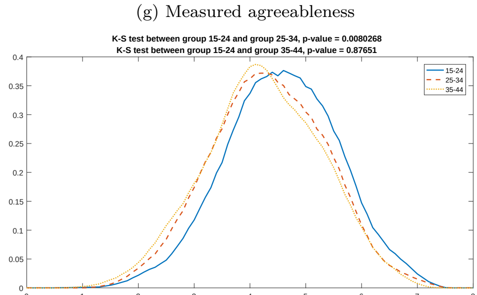
(e) Measured extraversion



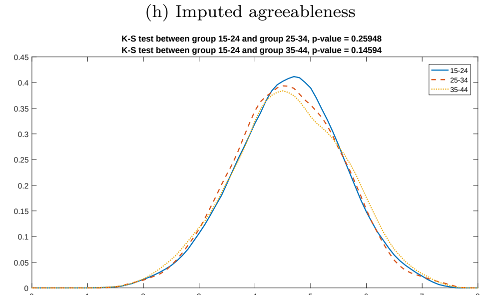
(f) Imputed extraversion



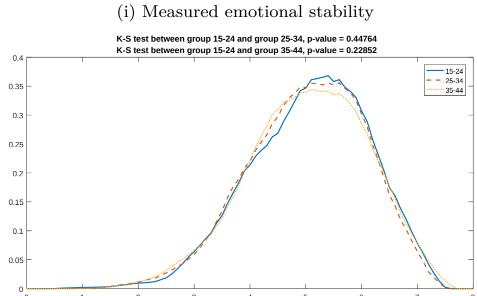
(g) Measured agreeableness



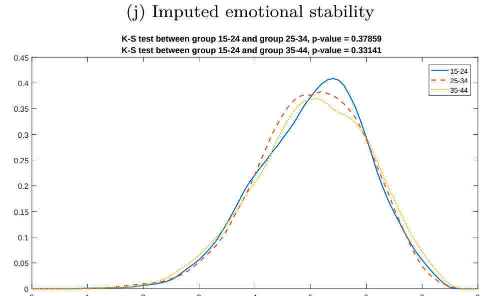
(h) Imputed agreeableness



(i) Measured emotional stability

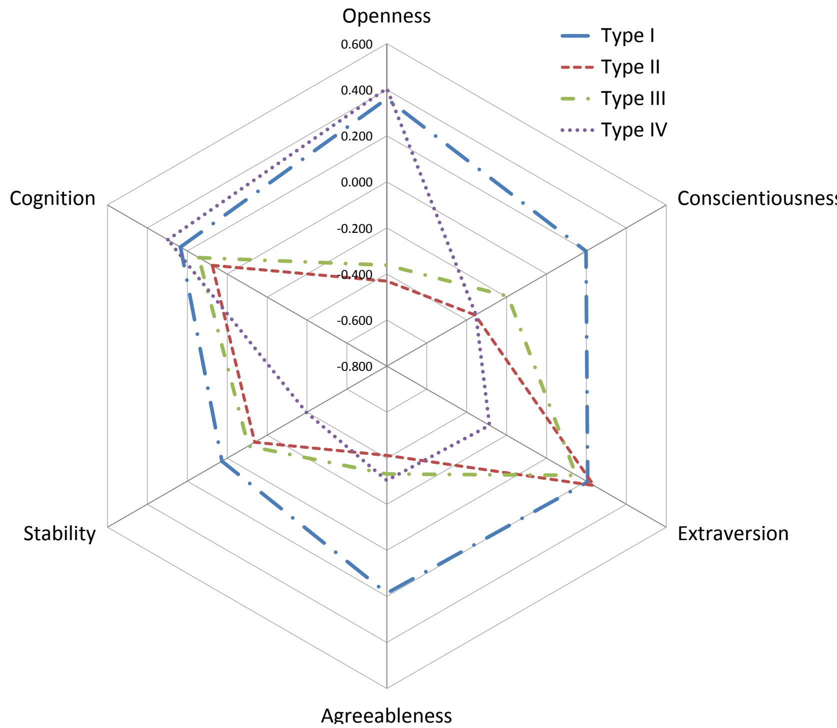


(j) Imputed emotional stability



Note: This figures display the comparison of "big five" between measured distributions and imputed distributions from different age groups. The left panel is the reported "big five" distributions when individuals are actually measured, while the right panel is the distributions of imputed initial distributions at age 15. In each figures, solid blue distribution represents the age group between 15-24. Dashed red distribution represents the age group between 25-34. Dot origin distribution represents the age group between 35-44. We compare distributions using two-sample Kolmogorov-Smirnov test. Their p-values are reported on the top of each figure. Data source: HILDA 2005, 2009 and 2013. Males whose personality traits are measured at least one time between 15-44.

Figure 7: Average personality traits and cognitive ability by type



Note: This radar chart provides a graphical depiction of the average levels of personality traits and cognition by type. Each equi-angular spoke ("radii") represents one dimension of personality traits. All values of personality traits and cognitive score are standardized to be zero mean and unit standard deviation.

Figure 8: How the type distribution changes with age