The Effects of Education, Personality, and IQ on Earnings of High-Ability Men

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Abstract

This paper estimates the internal rate of return (IRR) to education for men of the Terman sample, a 70-year long prospective cohort study of high-ability individuals. The Terman data is unique in that it not only provides full working-life earnings histories of the participants, but it also includes detailed information on each subject, including IQ and measures of latent personality traits. Thus, we can identify the treatment effect of education on earnings using a generalized matching procedure, and we show the importance of personality on educational attainment and lifetime earnings.

The internal rate of return to education differs from the Mincer coefficient which is traditionally reported. Since we observe lifetime earnings data, our estimates of the IRR are direct and do not depend on the assumptions that are usually made in order to justify the interpretation of regression coefficients as rates of return.

We show that even for these high-ability males, the returns to education beyond high school are sizeable. For example, the IRR for obtaining a bachelor's degree over a high school diploma is 11.1%, and for a doctoral degree over a bachelor's degree it is 6.7%. These results are unique because they highlight the returns to high-ability and high-education individuals, who are not well-represented in regular data sets.

Furthermore, our results highlight the importance of personality and intelligence on our outcome variables. While the inclusion of these does not alter the IRR estimates, we find that personality traits similar to the Big Five are significant factors in the determination of lifetime earnings. Even holding the level of education constant, measures of personality traits have significant effects on earnings. Similarly, incrementally higher IQ is rewarded in the labor market, independently of education - even in the range of 140 to 200. Most of the effect of personality and IQ on life-time earnings arise late in life, during the prime working years.

Contents

1 Introduction

This paper estimates the causal effect of education on earnings, and the corresponding rate of return to education, for a sample of high-ability men. At the same time, we show how measures of personality influence lifetime earnings both directly and indirectly through educational choice.

The Life-Cycle Study of Children with High Ability,[1] hereafter referred to as the "Terman data," is unique and enables us to address several issues which are generally hard to investigate. The study provides rich background information on the participants, as well as detailed measures of personality and interest. Additionally, it is one of the longest prospective cohort studies in existence,[2] so that the subjects' full earnings histories are known.[3] The participants were selected on the basis of having an IQ above 140, and were followed from 1922 to 1991 with surveys every 5–10 years, starting when they were on average ten years old.

We can establish causality of education using the rich set of control variables, including IQ and latent personality traits, and analyze the full lifetime effects on earnings through the longitudinal aspect of the data. For education, the lifetime effect is summarized by the internal rate of return, which we can compute directly instead of just approximating it. For personality, access to the long follow-up means that we can follow the evolution of the role of personality on earnings. Generally, the effects of personality on earnings during the early stages of a career are only a fraction of what they are after age 40.

The Terman sample lets us highlight a few facts: Even in a high-ability group, education has positive returns. At the same time, we do not find much evidence that the production function of marketable skills is convex in ability. Furthermore, we find that even in this top-IQ group, IQ increases earnings directly as well as indirectly through schooling choices.

[1] Terman and Sears (2002a,b); Terman et al. (2002a,b)

[2] Friedman et al. (1995)

[3] In a Web Appendix, we provide an extensive description of how the education and earnings histories, as well as the marriage histories, were constructed: http://home.uchicago.edu/~mgensowski/Terman/0TermanApp.pdf

Finally, personality has clear incremental effects on earnings, beyond IQ and schooling.

We contribute to the literature in three ways. First, we establish causality of education on earnings through a matching procedure. Second, we estimate the *true* internal rate of return to education for the Terman sample, which depends on having the full earnings histories. Third, we show the complete life-time effects of latent personality traits on earnings, which also depends on the availability of a long follow-up.

The first contribution of our paper is the identification of the causal effect of education, which we establish with a matching procedure. Matching is made possible by the richness of the Terman data. Establishing causality between education and higher earnings has been at the center of many efforts in the field. If unobservable variables (most prominently, "ability") positively influence the amount of education obtained and are independently rewarded, then the coefficient on education overstates the direct causal effect of education on earnings when one fails to control for such variables. Since schooling is the result of optimizing behavior, and since the decision maker has more information about himself than the economist, the amount of schooling that an individual obtains is likely to be endogenous.[4] Matching assumes that

[4]The two main approaches to deal with the issue of endogeneity of the schooling decision discussed in Card (1999) are instrumental variables and twin studies. The IV analyses are based on the premise that there are variables that affect the cost of schooling, but not the benefit. They exploit institutional sources of variation in schooling, i.e. the minimum school leaving age, tuition costs, or the geographic proximity of colleges. The most well-known articles are by Angrist and Krueger (1991), Staiger and Stock (1997) (discussed by Bound et al. (1995) and Bound and Jaeger (1996)), Kane and Rouse (1993), Card (1995), and Angrist and Krueger (1992). The instruments used vary greatly in quality – see Carneiro and Heckman (2002) for a critical analysis. IV estimates are generally larger than the corresponding OLS estimates. It is unclear how to interpret the point estimates, because with heterogeneous returns to schooling, the point estimate of the schooling coefficient is a weighted average of the idiosyncratic marginal benefits for the persons whose schooling choices were affected by the instrument. Papers using twins or brothers are based on the fact that twins or brothers share at least one common component of the unobservable ability variable. For the most prominent works after Chamberlain and Griliches (1975) and the survey by Griliches (1979), see the papers on monozygotic twins by Ashenfelter and Krueger (1994); Ashenfelter and Rouse (1998); Rouse (1999), and Behrman and Taubman (1994). Measurement-error corrected within-family estimates were slightly smaller than the simple OLS coefficients. The remaining question is whether twins' abilities and skills are truly identical, especially considering personality traits. These factors are important inputs into schooling and valued in the labor market (Bowles et al., 2001; Heckman et al., 2006). Therefore, estimates of the effect of schooling on wages that control for genetic background factors can still be biased. Furthermore, research by Fraga et al. (2005) and others shows that even in monozygotic twins, epigenetic differences arise during the lifetime. Heckman and Vytlacil (2007) explicitly discuss structural models (the control function approach), matching, and other treatment effect estimators, and how they can be put into a common framework of marginal treatment effects.

the researcher has all relevant control variables at his disposal, and that the participant's selection into treatment can be represented as a selection on these variables.

The Terman data is optimal for estimating the treatment effect with matching. As we argue below, the sample itself is quite homogenous. In addition, the data provides a large set of essential observable background variables: the respondent's childhood health, parental background, family environment, and teenage health. The data also includes the respondent's cognitive ability (IQ) and measures of latent personality traits. Controlling for IQ addresses the ability bias concern. "Psychic costs" are considered to be another important determinant of schooling choice, and economists generally cannot measure these costs. We approximate psychic costs by explicitly taking into account measures of personality, such as conscientiousness and extraversion. These traits are highly relevant for both schooling choice and earnings, and are thus an integral part of the matching procedure.[5]

The second contribution we make is to compute the internal rate of return instead of only interpreting the coefficient on schooling in a wage equation as "the rate of return." Even though the return to education is one of the central ideas in labor economics, most articles on the subject do not actually estimate the internal rate of return. The coefficient on years of schooling in a Mincer equation, which is hedonic in nature, can only be interpreted as the rate of return under stringent conditions, which have been tested and rejected previously (by Heckman et al. (2006, 2008). In our analysis, we compute the internal rate of return to

[5] The Terman data has been used extensively by psychologists, but only scarcely by economists. Known to us are only Becker et al. (1977); Hamermesh (1984); Michael (1976); Tomes (1981) and Leibowitz (1974). The only economic paper that uses the Terman sample to analyze the effect of education attainment on earnings is Leibowitz (1974). This paper estimates a Ben-Porath model of investment in human capital, in the pre-school, school, and post-school periods. Income is modeled as being derived from the rents on human capital in the form of ability and home, schooling, and postschooling investments. The estimation, however, deals with ability and home investments separately, not in one equation. It is in fact an earnings equation at three points in time (1940, 1950 and 1960). "Home investments" are only proxied by parents' education and family income. The measure of schooling is "years of schooling," converted from the categorical data on degrees obtained. Including childhood IQ as a covariate in the wage equation does not alter the coefficient on education by much. The coefficient on years of schooling ranges from .063 (in 1940) to .075 (in 1960). Estimates are very similar for the three OLS specifications - standard Mincer regression with only schooling and a quadratic in experience; controlling for parents' education and family income; or controlling for childhood IQ. Our paper has a different goal, and uses a more refined set of control variables than Leibowitz. We do not claim to estimate a Ben-Porath investment model, and we use earnings from all years instead of only a few.

obtaining one degree versus another instead of assuming that earnings are linear in years of schooling. The earnings histories in the Terman data are complete, so we know the length of the working life. The explicit cost of college is taken into account, as well as tax rates by marital status. The indirect effects of education on earnings, for example through marriage, longevity and the labor-leisure choice, are also accounted for in our analysis. See Figure 1 for the average earning of males and females by level of education.

Our third contribution is to show how the effect of personality on earnings varies throughout the men's working lives. We find that without access to long follow-up data, the estimated effect would be understated. Note that even though the Terman sample has a restricted range of IQ, there is substantial variation in personality.

The paper proceeds as follows. First, we describe the matching approach, and argue how this identifies the causal effect of education on earnings. In Section 2 we describe the matching procedure and variables used. Section 3 discusses the difference between the Mincer coefficients and the internal rate of return to education, and presents our estimates of the rates of return to all education pairs. Section 4 addresses the effect personality has on life-time earnings, both directly and indirectly through education.

2 Identification through Matching

Our empirical analysis relies on matching to identify the causal effect of education on earnings. The invoked matching assumptions guarantee identification of the average treatment effect. For a discussion of the method, the potential outcomes representation is useful. Model each person's outcomes (i.e. his earnings) in two states 0 and 1 as

$$Y_1 = \mu_1(X, \theta) + \varepsilon_1,$$
$$Y_0 = \mu_0(X, \theta) + \varepsilon_0.$$

Here, treatment (state 1) denotes the higher education level. Therefore, Y_1 corresponds to earnings one would have with higher education, and Y_0 corresponds to earnings one would have with lower education. $\mu_k(X, \theta)$ is the expected mean earnings in treatment state k, conditional on observed background variables X and latent variables θ. Note that Y_1 and Y_0 are *potential* outcomes only; they cannot be both observed for the same person. Let D indicate the treatment. Then, we observe

$$\begin{aligned}
Y &= DY_1 + (1 - D)Y_0 \\
&= Y_0 + D(Y_1 - Y_0) \\
&= \boldsymbol{\mu_0}(X, \boldsymbol{\theta}) + \varepsilon_0 + D(\boldsymbol{\mu_1}(X, \boldsymbol{\theta}) + \varepsilon_1 - \boldsymbol{\mu_0}(X, \boldsymbol{\theta}) - \varepsilon_0).
\end{aligned}$$

When a person has the higher schooling level, $D = 1$ and we observe Y_1. When he has the lower schooling level, $D = 0$ and we observe Y_0. In the potential outcome approach, a treatment's impact is given by the comparison of the observed outcome to the other, counterfactual, outcome: $\Delta = Y_1 - Y_0$. However, we only observe outcome $Y = DY_1 + (1 - D)Y_0$, and thus there exists an evaluation problem (we observe one individual in only one of the possible treatment states). Also, there is a selection problem since individuals select into treatment based on potential outcomes. Therefore,

$$(Y_0, Y_1) \not\perp\!\!\!\perp D$$

and $E(Y_1 \mid D = 1) - E(Y_0 \mid D = 0) \neq E(Y_1 - Y_0)$.

2.1 Matching Assumptions

Matching assumes that conditioning on observables X eliminates the dependence between (Y_0, Y_1) and D. The two matching assumptions are

$$(Y_0, Y_1) \perp\!\!\!\perp D|X \tag{M-1}$$

$$0 < \Pr(D = 1|X) < 1. \tag{M-2}$$

Propensity score matching, a well-known variant of matching, reduces the dimensionality. The propensity score $P(X) = \Pr(D = 1|X)$ is the probability of participation, or the probability of obtaining the higher education level. Rosenbaum and Rubin (1983) prove that when the two matching conditions (M-1) and (M-2) hold, we can also express the first as

$$(Y_0, Y_1) \perp\!\!\!\perp D|P(X). \tag{M-1'}$$

Now assume that we can observe, or have access to, otherwise latent variables θ. Using these variables in the set of conditioning variables allows us to relax assumption (M-1). With such information, the following is more appropriate:

$$(Y_0, Y_1) \perp\!\!\!\perp D|X.\theta \tag{M-1''}$$

(M-1”) can again be modified to condition on $P(X, \theta)$ instead of X and θ separately.

Based on the potential outcome model outlined above, the treatment effect at each age is

$$\Delta_t = Y_{1,t} - Y_{0,t} = \boldsymbol{\mu_1}(X_t, \boldsymbol{\theta}) - \boldsymbol{\mu_0}(X_t, \boldsymbol{\theta}) + \varepsilon_{1,t} - \varepsilon_{0,t}. \tag{1}$$

The choice of modeling $\boldsymbol{\mu_1}(X_t, \boldsymbol{\theta})$ and $\boldsymbol{\mu_0}(X_t, \boldsymbol{\theta})$ remains. The functional form we will employ for this paper is the following linear model, where coefficients are equal in both treatment states[6] and outcomes are modeled as

$$\mu_1(X_t, \theta) = c_{1,t} + X_t\beta_t + \theta\delta_t,$$
$$\mu_0(X_t, \theta) = c_{0,t} + X_t\beta_t + \theta\delta_t.$$

Estimation of the treatment effect consists only of regressing the observed Y on the observed X, latent θ, and the treatment indicator:

$$Y_t = X_t\beta_t + \theta\delta_t + D\overline{\Delta}_t + c_{0,t} + e.$$

Here, $\overline{\Delta}_t$ is the average treatment effect of D on Y_t at time t. In the case of multiple treatment states, notably the five education levels from high school diploma to doctoral degree, D is a matrix of treatment indicators.

Our measures of θ are the predicted factor scores. Thus, we introduce error by using these factor scores rather than the true factors. However, knowing the factor model, we can characterize the measurement error and correct the coefficients on the factors accordingly (see, Iwata, 1992, for example,).

Matching does not model the decision process. It relies on the data being sufficient to make the decision variable conditionally independent from the distribution of outcomes.[7] Assumption (M-2) can be verified, and is usually no cause of debate (we verify it in the

[6]This choice is the result of a tradeoff between flexibility and measurement error correction. Nonparametric matching does not make the strong functional form assumptions as linear separable parametric forms do. The latter versions, on the other hand, allow for a correction of attenuation bias. Measurement error is introduced into our estimation by using predicted factor scores instead of the true factors. However, the precise form of the attenuation bias is known, and thus can be corrected using the covariance matrix of the true factors that are computed during the factor estimation. Iwata (1992), for example, describes this correction method. In the Web Appendix, we present treatment estimations that test three different functional forms for $\boldsymbol{\mu}(X_t, \boldsymbol{\theta})$: local linear matching (kernel matching), a linear separable model for each treatment state, and the common coefficient model. Interestingly, the respective treatment effect estimates are almost identical. Therefore, we chose the latter which is computationally very simple and allows for the measurement error correction.

[7]Structural models of the schooling decisions have been estimated by, for example, Keane and Wolpin (1997), Eckstein and Wolpin (1999), or Belzil and Hansen (2002). The technology of skill formation has been modeled in Cunha and Heckman (2007); Cunha et al. (2006). Hansen et al. (2004) show how schooling and ability measures interact.

Web Appendix). Assumption (M-1) (statistical conditional independence), however, implies that conditional on X, the marginal return equals the average return. This is a strong behavioral assumption, and as Heckman and Vytlacil (2007) note, "Many economists do not have enough faith in their data to invoke it." The Terman data, however, allows us to match subjects much more closely than can usually be done. We now argue why.

2.2 IQ and Personality Factors

We match not only on observable variables, but also on latent traits. Most models concerned with ability bias in education are of the "single-factor" type, with an underlying hierarchical interpretation of ability. We account for multiple types of ability, notably IQ and a vector of personality traits. Denote the vector of these traits θ.

IQ was measured at study entry in 1922, and was the basis for inclusion in the Terman sample. [8] The data gives us only one IQ score, so in order to control for possible differences in measurement in our analysis, we include an indicator for the "Terman Group Test" and an interaction of the score with this indicator.

We define the included latent personality traits similarly to the Big Five taxonomy, notably Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism (OCEAN). While our traits are conceptually very close to the Big Five personality traits, they are not measured with the same inventory. However, inspection of the items shows the close correspondence. Furthermore, Martin and Friedman (2000) have shown that Conscientiousness and Extraversion from the Terman questionnaires correspond closely to the Big Five traits.

To quantify the personality traits, we compute factor scores using a three-step estimation procedure, as outlined in Heckman et al. (2010). This estimation procedure, which will be explained in more detail below, extracts the factors from personality ratings in 1922, 1940, and 1950. We use teacher-, parent-, and self-ratings from these surveys[9]

[8] Most students took the Stanford-Binet IQ test. About 30% of the students took another IQ test, the "Terman Group Test", specifically designed for screening these high achieving children. For a more detailed description of the tests, see Chapter I in Terman and Sears (2002a).

[9] See our discussion of whether personality can be considered a causal factor in the determination of

The two personality traits from 1922 are Openness and Extraversion. The factor score for Extraversion is extracted from the average of parents' and teacher's ratings of the subject's "fondness for large groups," "leadership," and "popularity with other children." The factor score for Openness is extracted from ratings of the subject's "desire to know," "originality," and "intelligence." [10]

The dedicated items for the factors of Conscientiousness, Agreeableness, and Neuroticism are based on self-ratings in 1940 and 1950. Where items from both years are available, we use the average. In a few cases, we use mean-imputation for missing item responses. The self-ratings of personality traits from 1940 and 1950 are on an 11-point scale, with 11 being the high end of the trait described. In 1940, the subjects filled out an extensive list of personality items of the Bernreuter personality inventory. These items are questions about usual behavior and feelings that can be answered "yes," "no," and "?."

Conscientiousness is constructed from self-ratings of "persistence" and "definite purposes," as well as the Bernreuter items "Do you enjoy planning your work in detail?" and "In your work do you usually drive yourself steadily?" Neuroticism is based on the measurements on "moodiness," "sensitive feelings," "feelings of inferiority," and the Bernreuter items "Are you much affected by the praise or blame of many people?," "Are you frequently burdened by a sense of remorse or regret?," "Do you worry too long over humiliating experiences?," "Are you feelings easily hurt?" Agreeableness is based on the ratings of "easy to get along with" as well as the Bernreuter items "Do you usually try to avoid arguments?," "Are you always careful to avoid saying anything that might hurt anyone's feelings?," "Do

wages. This caveat clearly applies more so for the factor scores constructed from the self-ratings in 1940 and 1950 than for the teacher and parent ratings of 1922, since these are pre-market ratings. The fact that these ratings are so early constitutes at the same time a drawback: contemporaneous personality determines wages, not the personality of when individuals were 10 years old. Personality may evolve over the life cycle, and by using early measures one disregards this possibility.

[10]Due to the phrasing, it might seem as if Openness and IQ measure the same underlying trait. Note that the IQ test is a direct test of the subject's cognitive ability, while the parents' and teachers' ratings describe their impressions of the child. Furthermore, several measurements of these impressions combine to the factor defined by psychologists as "Openness." Hogan and Hogan (2007) define the Big Five Openness as the degree to which a person needs intellectual stimulation, change, and variety. Openness is indeed correlated with IQ, at .16 (significantly different from zero), but not perfectly.

you often ignore the feelings of others when doing something that is important to you?".

In this paper, we use the three-step estimation procedure outlined in Heckman, Malofeeva, Pinto, and Savelyev (2010). In the first step, we use the measures for the multiple components of each personality factor to estimate the parameters of each factor's respective measurement system. We denote measures that capture factor j by $M^j_{m^j}$, where $m^j \in \mathcal{M}^j$. There may be a different number of measures for each of the factor types $j \in \mathcal{J}$. The measurement systems are of the form

$$\begin{aligned} M^j_1 &= \nu^j_1 + \theta^j + \eta^j_1, \\ M^j_{m^j} &= \nu^j_{m^j} + \varphi^j_{m^j}\theta^j + \eta^j_{m^j}; \qquad m^j \in \mathcal{M}^j \setminus \{1\}, \forall j \in \mathcal{J}, \end{aligned}$$

where the factor loading associated with the first measure of each factor is normalized to unity to set the scale of the factors. At the end of the first step, these parameters are used to predict factor scores by the Bartlett (1937) method. In the second step, we use the factor scores as covariates in our matching analysis. Finally, in the third step, we adjust the coefficients on the factor scores for the bias introduced by using the predicted factor score instead of the true factor. The intuition behind this adjustment is similar to the standard attenuation-bias formula. The formula for the attenuation through the predicted factor is a function of the covariance matrix of the true factor as well as the measured factor score. The latter is readily available, and the former can be extracted from the factor estimation itself.

These personality traits are both predictors of educational choice and explanatory variables in the wage outcome equations. Their effects on education and wages will be discussed in detail in Section 4.

2.3 Matching Variables

In addition to the availability of high quality measures of latent factors, there are two other elements of the Terman data which render it ideal for matching: a very homogenous sample and the availability of a large set of relevant observable background variables.

Subjects are already approximate matches due to the homogeneity of the sample. All subjects are highly intelligent and living in California at the time of the study's inception. They are Caucasian and generally lived in advantageous environments (the vast majority are from middle-class families).

Second, the Terman data provides a large number of covariates, allowing us to control for a wide array of essential variables that influence both education and labor market success. Respondents are matched on IQ score at the beginning of the study, father's and mother's backgrounds (education, occupation, social status, region of origin, age at birth of subject), family environment (family's finances when growing up, number of siblings, birth order), and early childhood health (birthweight, breastfeeding, sleep quality in 1922). Additional controls are birth cohort group (birth year 1904-10 or 1911-15), and whether the subject was active in combat in World War II.[11] Table 1 presents descriptive statistics for the sample and all background variables used.

Third, we control for the fundamental latent personality types of the individuals, as described in section 2.2. Personality traits are not only relevant to the educational choice, but also influence earnings directly.

3 The Rate of Return to Education

We will now discuss the rate of returns to education for the men in the Terman sample. First, we discuss what this is formally, and why it differs from what is commonly called "return to education" in the literature. Then we show that even for men at the high end of

[11] While there are more covariates available, in order to avoid overfitting, we selected a group of the most relevant characteristics and background variables.

the ability distribution, the rates of return to education are substantial.

3.1 The Internal Rate of Return

The rate of return to an investment is, in simple words, the discount rate that sets the net present value (NPV) of the earnings streams to zero. To compare two mutually exclusive investments, one takes the difference between the two earnings streams and again finds the discount rate that sets the NPV to zero.

In the case of education as an investment, the treatment effect corresponds to these net earnings streams. Given our matching assumption described in Section 2, we identify the average treatment effect at each age. The longitudinal aspect of the Terman data allows us to observe this for each individual. Denote the individual treatment effect at age t as δ_t, i, and the average treatment effect $\overline{\Delta_t} = E[Y_{1,t} - Y_{0,t}|X_t, \theta_t] = ATE$.[12] Then, the IRR, ρ, is defined as the solution to the following polynomial:

$$\sum_{t=18}^{75} \frac{\overline{\Delta}_t}{(1+\rho)^{t-17}} = 0, \tag{2}$$

where age t ranges from 18 to 75.

Instead of finding ρ, the net present value assumes a fixed interest rate, r, and reports the discounted sum of earnings differences. For the purposes of our examples, we use a discount rate of 5% whenever we report the NPV.[13]

[12] Note that we are interested in all direct and indirect effects that schooling has on *lifetime earnings*. These comprise effects of education on the labor-leisure choice (including retirement or unemployment) and longevity. Since we are not estimating a pricing equation of human capital, we use a comprehensive earnings measure (annual earnings in levels) that also reflects the intensity with which human capital is used.

[13] While the IRR is useful as a summary of an investment project (in a single number), it has certain shortcomings. When the IRR is compared to the current interest rate, one can "read off" whether the investment should be undertaken – as long as one is only interested in the profitability of *one* project, and as long as this project's cash flow changes from positive to negative only once. For comparison of two mutually exclusive projects, the NPV is a better guide. It does not suffer from the scale problem and the timing problem as the IRR does (for a discussion and examples, see Chapter 6 of Ross, Westerfield, and Jaffe (2001)). Finally, note that neither the NPV nor the IRR take into account uncertainty, psychic costs of college, or differential costs of funding.

3.2 Interpreting the Mincer coefficient as the Rate of Return

The return to education is one of the central ideas in labor economics.[14] However, most articles on the subject do not actually estimate the internal rate of return. Instead, they follow common practice in estimating a Mincer-type equation and "reading off" the return to education as the coefficient on years of schooling (Altonji and Dunn, 1996; Glewwe, 1996; Griffin, 1993; Harmon, 2003; Johnson and Chow, 1997; Nevile and Saunders, 1998; Palme and Wright, 1998; Psacharopoulos and Patrinos, 2002; Ryoo et al., 1993; Siphambe, 2000; Trostel, 2005, see, for example).[15] In fact, Mincer had provided a model and corresponding assumptions under which the coefficient was indeed the internal rate of return. The assumptions that allow the interpretation of the Mincer coefficient as the rate of return are linearity of earnings in years of schooling, constant working life, and no explicit or psychic costs of college. These assumptions are not tenable, and therefore the practice of equating the coefficient on years of schooling with the rate of return has been subject to criticism, notably by Heckman et al. (2006, 2008) As they show, the Mincer coefficient is not equal to the rate of return; even using only synthetic cohorts.

In our analysis, we use a true cohort analysis and can thus compute the ex-post internal rate of return to one degree versus another. This way, we bypass all assumptions necessary to interpret the Mincer coefficient as the rate of return - by computing it directly. Instead of assuming that earnings are linear in years of schooling, we compare degrees. The earnings histories in the Terman data are complete, so we know the length of the working life. The

[14] It was rendered popular by Mincer (1974) who estimated Becker and Chiswick (1966)'s model, in which the coefficient on schooling could indeed be interpreted as a rate of return. Belzil and Hansen (2002) note "A World Wide Web survey of the most recent literature indicates that, since 1970, more than 200 published articles or working papers (set in a reduced-form) have been devoted to the estimation of the return to schooling or surrounding issues." For reviews of these estimations in the literature, see Psacharopoulos (1981), Psacharopoulos and Patrinos (2004), Willis (1986), and Card (1999).

[15] In doing so, they follow Willis (1986) who wrote that "the simple Mincer-type earnings function does a surprisingly good job of estimating the returns to education."

explicit cost of college is taken into account,[16] as well as tax rates by marital status.[17] The indirect effects of education on earnings, for example through marriage, longevity and the labor-leisure choice, are also accounted for in our analysis.

Even though the Terman data is longitudinal, we can estimate the Mincer equation as if the data were cross-sectional.[18] The Mincer rate of return as estimated from the Terman data is only 7.2%.

Before obtaining the true rate of return for the Terman males, we need to identify the treatment effects of different education levels.

3.3 Treatment Effects of Education, Pairwise IRRs

Recall that the treatment effect of education tells us, in a counterfactual sense, how much a person would have gained or lost as a result of obtaining more or less education. It describes by how much having the higher degree, in comparison to the lower level of education, improves average earnings at each age, holding everything else constant. The treatment effects of all education pairs are shown in Figures 2 to 6.

The treatment effect of higher education is negative in the men's early years, since those obtaining higher education are still attending school while their peers with less education are already out of school and in the job market. Later, during the prime working years, the positive effect of education is substantial. This is a standard result in the literature. The outcome variable is annual earnings after tax and tuition, in 2008 U.S. Dollars. The tax

[16] From a detailed education history that includes the name of the college or university attended, we impute the cost of schooling. The participants also gave information on scholarships and fellowships, which is taken into account in this computation. Note that the costs considered here are purely pecuniary and exclude psychic cost, for example.

[17] The tax rates and corresponding brackets are taken from form US-1040 by the IRS, collected by the Tax Foundation at http://www.taxfoundation.org/publications/show/151.html. We use the marital status at each age, as determined by the marriage history we construct, in order to apply different tax rates for singles and married participants. Unfortunately, we only have one measure of income, so the tax brackets are determined based on earnings (or family earnings) only. This possibly understates the participants' tax dues, if they had substantial non-wage income.

[18] For this comparison we use all observations in the treatment-estimation sample, ages 16-75, as if they were from a cross-section. Years of schooling are imputed from degrees. Experience is approximated by substracting six and the number of years of schooling from the participant's current age, as is often done in the literature.

rates used are a function of marital status (married or single). Tuition was subtracted from earnings at each year that college was attended, at both the undergraduate and graduate level.[19]

The IRRs and NPVs corresponding to the treatment effects are summarized in Table 3. In comparison to having a high school diploma, obtaining a bachelor's degree increases earnings by $111,788 over a lifetime, if the difference in earnings is discounted at 5%. The corresponding IRR is 11.1%. This means that even for the highly talented Terman men with IQs above 140, going to school substantially contributed to increasing their lifetime earnings, and the rate of return to this investment exceeds that of the market.[21] In comparison to a high school diploma, having completed only some college courses leads to only slightly higher earnings throughout one's life, but since the investment costs are very low, the corresponding rate of return of 9.0% seems relatively high. Since the investment period for obtaining a master's degree or a doctoral degree is longer than for a bachelor's degree, the rates of return for these education levels in comparison to a high school diploma are lower than the 11.1% figure from the bachelor's degree. The IRRs are 8.0% for a master's degree and 8.9% for a doctoral degree over a high school diploma. Note that at almost identical rates of return, the doctoral degree nevertheless leads to much higher discounted earnings gains than the master's degree ($79,867 vs $144,491). The rates of return of having a college degree or higher in comparison to "some college" are almost equivalent to the returns over "high school only." The difference between the two base-line education levels only appears in present value terms — the discounted gains in comparison to "some college" are around $25,000 lower than in comparison to "high school diploma." Note that this is similar to the earnings difference between high school and some college. In comparison to having a

[19]For tuition rates, we drew on de Gruyter, W., ed. (1948) and Hurt, H., ed. (1949) from 1920 to 1940. Details on how the tuition data was constructed are given in the Web Appendix[20]. We have made two implicit assumptions about tuition payments: 1. by subtracting them at the time of college attendance, we exclude smoothing out of the expense; and 2. we assume that graduate students paid the full tuition as noted in the aforementioned sources. Our results change in only minor ways when we relax both assumptions.

[21]For example, the S&P 500 annualized return from 1928 to 1985 (when the Terman men were on average 18 - 75 years old), is about 6%.

bachelor's degree, having a master's degree has almost no return. However, obtaining a doctoral degree over a bachelor's degree does increase lifetime earnings, corresponding to an IRR of 6.7% and a present value of the difference of \$32,703. This NPV seems rather low because most of the gains arise late in the working life and are discounted heavily. The return to having a doctorate over a master's degree is high (12.5%). In this case, both groups have relatively long investment periods, but men with doctoral degrees have higher earnings. Thus, in this comparison, the investment is low and the return is high.

As explained in the previous section, the IRRs should not be used for determining the optimality of one education investment versus another, in comparison to a third education level which is the baseline.[22] In principle, one compares one IRR to the prevalent interest rate. However, this type of comparison ignores the dynamic aspect of schooling and the sequential revelation of uncertainty.[23] Our analysis is explicitly ex-post and considers rates of return in a static setting.

We can draw two conclusions from these results. One is that even in a very high ability group, education adds skills that are valued in the marketplace. The returns to schooling are real, and ability bias cannot be responsible for the type of returns we find. The second conclusion is that there is little evidence for a convexity of the production function of skills in

[22]For the reader that is startled by the "nonlinear" pattern of some of the pairwise IRRs, let us consider an example. For example, if for males the return of a master's degree versus a bachelor's degree is only 1.2%, how can it be that the IRR of getting a doctoral degree versus a master's degree is 12.5%, but a doctoral degree versus a bachelor's degree is only 6.7%? Shouldn't the two IRRs be more similar, and if anything the IRR of a doctorate versus a master's degree a little lower? To understand these numbers, examine the graphs of the pairwise treatment effects. We see that initially, as they pursue more schooling, those with a master's degree have negative treatment effects. These negative effects are only barely offset by slightly higher earnings late in life. Thus, even though there is a difference between the two earnings streams, the IRR is very small. Now if we compare a doctoral degree to a bachelor's degree, the pattern is similar, except that the men with a doctoral degree have a sizeable positive treatment effect later in life. Thus, the IRR is greater than for a master's degree versus a bachelor's degree. But if we proceed to the comparison of a doctorate versus a master's degree, note that men in both groups will spend more time in school, and thus forego earnings. In comparison to the men with a master's degree, the men with a doctorate are *not* losing out as much as in comparison to one with a bachelor's degree who start earning earlier. However, those with doctoral degrees will proceed to have substantially higher earnings. Thus, since there are almost no initial costs of getting a doctorate in comparison to getting a master's degree, but sizeable gains, the IRR of a doctorate versus a master's degree is sizeable (12.5%).

[23] See for example Heckman et al. (2006) for a discussion of the problems and particularities associated with sequential resolution of uncertainty. The option value of schooling has been analyzed, for example, by Heckman and Urzua (2008).

ability. If there was such a convexity (that is, more able individuals learn more from school than less able individuals), we would have expected higher returns than those we observe.

4 The Effects of IQ and Personality Traits on Lifetime Earnings of Males

So far, we have focused on the returns to education, using personality and IQ only as control variables. However, personality and IQ are clearly interesting in their own right, and this section deals with these variables explicitly. First of all, we show that the IRR estimates of Section 3 are not much altered when we omit the controls for personality traits and IQ. Then, we ask very generally "How do personality and IQ affect life-time earnings of the Terman men?" After briefly analyzing the overall effect of personality on total earnings, we focus on the two main channels: 1. personality traits affects educational attainment and thus affect wages indirectly through education, and 2. personality traits are rewarded independently in the labor market and thus affect wages directly. Section 4.3 presents results on the role of personality traits in educational choice, and Section 4.4 shows the "gains to personality" holding education constant.

4.1 The IRR not accounting for IQ and Personality Traits

How much would our estimates of the rates of return change if we did not have access to the personality factors and IQ? Table 4 shows results from the matching procedure without these covariates. We still include the full set of background variables, but we do not include the latent personality traits or IQ. The left half of Table 4 shows the IRRs from this specification, and the right half shows the bias in the IRRs from this reduced regression. The overstatement from the omitted variable bias is modest, usually in the 10-15% range.

Note that there is evidence of omitted variable bias when we exclude personality measures and IQ. Omitting personality and IQ is akin to, but slightly different from, ability bias in the traditional sense. The difference is that in the relatively IQ-homogenous Terman sample, omitting IQ does not bias the IRRs substantially. Separate analyses (not shown) prove that omitting the personality factor scores leads to a greater bias than omitting IQ. The modest bias in terms of IRRs that we find from omitting both personality measures and IQ is related to the way in which IRRs are estimated. The treatment effects in the prime-working years (age 40–60) are actually decreased by including the IQ and personality factors, but, due to discounting, the IRR does not pick up much of these later changes. The NPVs, on the other hand, do reflect the higher treatment effects. Note furthermore, in a preview of results in Section 4.4, that while the treatment effects are not greatly affected by the inclusion of personality factors and IQ, these variables do significantly influence wages directly.

4.2 The Total Effect of Personality and IQ on Lifetime Earnings

We now analyze how personality and IQ influence lifetime earnings. We use the sum of each individual's earnings from age 18 to age 75.[24] The first column of Table 5, "Total Effect," exhibits coefficients from the regression of lifetime earnings on personality traits and IQ only. The coefficients reflect a very general association between the personality variables in the Terman data and the male's lifetime earnings. No other covariates were controlled for. With this simple regression, Conscientiousness and Extraversion are positively associated with earnings, while Agreeableness and Openness are negatively associated with earnings (although Openness fails to be statistically significant in this very simple exercise). Our measure of Neuroticism does not have a clear association with earnings. It is remarkable that even in this very high-IQ sample, where the range of observed IQs is clearly restricted, IQ still has a positive and statistically highly significant association with lifetime earnings.

We call these simple associations "total effect" of latent personality traits and IQ on lifetime earnings since these traits affect lifetime earnings both indirectly through educational attainment (which we will explore more in the next section) and directly. We have already

[24]Here, we use the undiscounted sum of earnings, but a separate analysis with discounted earnings (at, for example 5%,) shows that all results presented here are maintained.

shown in Section 3.3 that schooling influences earnings substantially, independently of personality. Therefore, not conditioning on schooling in the regression of lifetime earnings on personality traits subsumes the effect of schooling in the personality variables' coefficients.

The second column, "Total Effect, with covariates" adds the full set of control variables. We thus control for background characteristics which might be correlated with personality, as well as schooling (still kept implicit). However, the estimates remain very similar.

Finally, the third column, "Direct Effect, given Education" presents the effect of personality on lifetime earnings, holding education constant. Again, it includes all covariates from the treatment effect analysis (parametric matching described in Section 2). The base line is "Doctoral Degree," and in comparison to this education level, all other educational categories have clearly lower lifetime earnings. The role of the personality traits and IQ are preserved. Conscientiousness and Extraversion still have large and positive effects on life-time earnings. Agreeableness has a negative lifetime "return", conditional on education.

Finally, note that even when controlling for rich background variables, IQ maintains a statistically significant effect on lifetime earnings. Even though the effect is slightly diminished from the un-controlled association of the first column, it is still sizeable. Malcolm Gladwell claims rather generally in his book "Outliers" that for the Terman men, IQ did *not* matter once family background and other observable personal characteristics were taken into account. While we do not want to argue that IQ has a larger role for the difference between 50 and 100, for example, than for the difference between 150 and 200, we do want to point out that even at the high end of the ability distribution, IQ has meaningful consequences.

One caveat about causality is in order. In contrast to the causal effect of education on earnings, there is a risk of reverse causality in the analysis of the effect of personality on earnings. Most researchers use early measures of personality and analyze the effects of these early measures on later outcomes, thus being certain that there is no reverse causality. We partially follow this approach by using early measures of Openness and Extraversion. However, the other personality traits are measured at a time where the men are already in their working lives. Thus, these measures are more relevant to the observed earnings, but at the same time we cannot exclude the possibility that, for example, a high score on Neuroticism is a *result* of one's position in the workforce. Therefore, while we do think of the results as showing earnings gains *due to* personality and IQ, we do not claim causality as we do in the case of education.

Another point of discussion concerns the role of personality in economic models. In this paper, we have followed the standard practice of just including personality variables as covariates in regressions, without modelling the manifest personality explicitly. Instead of this "standard methodology" one could model observed traits as a response to utility maximization under constraints, such as suggested in Almlund et al. (2011).

4.3 The Effects of IQ and Personality on Education

Several authors have analyzed how personality traits, and notably the Big Five factors, influence years of schooling obtained. For example, Almlund et al. (2011) summarize existing evidence on this relationship in datasets that are representative of the entire population (for the U.S., the Netherlands, and Germany). In these populations, Conscientiousness is always positively associated with years of education, while Extraversion, Agreeableness, and Neuroticism are negatively associated. While Openness exhibits a positive association, this effect is probably due to the correlation between Openness and IQ, which is not controlled for in these samples. When we run a simple regression of *years of schooling* on the personality variables and IQ, as well as the full set of background variables (not shown), we find that Conscientiousness unambiguously increases years of schooling. We can add to the results from the aforementioned representative samples that even at the high end of intelligence, Conscientiousness is still a separate and statistically significant predictor of schooling attainment. With IQ and the other additional background controls, the other personality factor scores are not statistically different from zero.

We believe, however, that discrete educational choices and degrees, the way we have analyzed them in the section on returns to schooling, are more meaningful than years of schooling completed. This holds all the more so at the high end of the educational spectrum. Therefore, we analyze educational choice using a multinomial logit model, which allows for five separate categorical outcomes. Having a high school diploma is the base level. Table 6 presents the relative risk ratios associated with each educational outcome in comparison to the baseline.

IQ has a positive influence on schooling attainment. A higher IQ in this sample makes it more likely to obtain higher schooling than a high school diploma. This is interesting given the highly selected sample we have; even for individuals with an IQ of 140 and over, having a higher IQ makes it less likely to remain in the lowest schooling category. Yet, this does not necessarily imply that having a higher IQ increases the odds of obtaining a master's degree rather than a bachelor's degree.

Conscientiousness predicts obtaining more education than a high school diploma as well; while only the comparison with the doctoral degree is statistically significant. It is intuitive to interpret Conscientiousness as lowering the psychic costs of education. In addition, the "future planning" element of Conscientiousness can be thought of as lowering the discount rate of future gains (recall that these gains are substantial, but accrue late in life). Also, a greater tendency to plan for the future could decrease the effort needed to imagine future outcomes and to correctly evaluate the costs and gains involved in the long-term investments of obtaining higher education. The effect of Conscientiousness is not only highly significant, but also linear. This means that higher Conscientiousness is always positive for educational attainment. This stands in contrast to the effects of the following two personality traits.

Neuroticism is only associated with one outcome, namely with *not* being in the category of "some college." Men who score higher on the Neuroticism scale are much less likely to be in this category than in the base outcome. Since this factor score is not significant for any other schooling level comparisons, we interpret this finding to mean that only men who are relatively stable emotionally remain in the vague schooling category without a college degree. The lack of importance of Neuroticism in the determination of schooling is somewhat surprising, especially in light of evidence from other sources. Notably, Locus of Control is often linked to Neuroticism, and an internal Locus of Control has been found by many authors to reliably predict higher schooling (see, for example Piatek and Pinger, 2010 or Baron and Cobb-Clark, 2010).

Extraversion seems negatively related with education, but in a non-linear fashion. Having a higher extraversion score decreases the odds of obtaining more than a high school diploma, everything else held constant, but only to a certain degree.

The factor scores on Openness and Agreeableness do not produce relative risk ratios that are statistically significantly different from 1 in the multinomial logit with high school as the base level. However, we can see that having a low score on Openness and a high score on Agreeableness would tend to increase the probability of either remaining in the "some college" category, or obtaining a doctoral degree.

We know that education has positive returns. Therefore, through the choice of educational level, personality indirectly affects lifetime earnings.

4.4 The Effects of IQ and Personality on Wages

How are earnings affected by personality traits, given the educational level? We have seen already in Table 5 that earnings and measures of personality traits are highly correlated. Since we are also interested in investigating when the "gains to personality" arise in the working life, a more detailed analysis is useful. In the treatment effect computations of Section 3, we controlled for the latent personality traits and IQ. Here, we discuss the coefficients on the factor scores that were obtained in these regressions. Specifically, we are interpreting the coefficients δ in equation (2.1). We interpret the coefficients as the direct effect of personality on wages. The effect of personality traits on educational attainment is controlled for by directly including the education indicators.

As expected, IQ has a positive and statistically significant effect on earnings for much of the life cycle (Panel a) of Figure 8. The effect of IQ, even in this select sample, is never negative. The positive gains from IQ start accruing relatively early in the working life, at age 30.

Openness has a negative effect on earnings in the Terman sample. Until age 40, there is no effect of Openness on earnings at all, only late in the working life does the negative effect materialize. Note that individually, the effects are not statistically significantly different from zero, although the direction is clearly negative.

Conscientiousness and Extraversion have the largest effects on earnings. Both traits clearly have a "return" in the sense that more conscientious and more extroverted individuals have higher earnings in the labor market, holding the level of education constant. As with IQ, the returns to these character traits are positive throughout the life cycle, although the largest gains appear in the prime working years, ages 45-55. Thus, if researchers have access only to earnings observations for the early working life, the gains from these two personality traits would likely be understated. Also note that while Conscientiousness increases earnings *directly and indirectly*, Extraversion has two different effects on lifetime earnings: It decreases them indirectly through its association with lower educational attainment, but increases earnings directly. Since the total effect (Table 5) of Extraversion on lifetime earnings is positive, the indirect effect must be small in comparison to the direct effect.

Agreeableness has a negative effect on earnings. As with Openness, these negative effects are mostly in the later working years. Had we analyzed the effect of personality on earnings only up to age 35, we would have completely missed this negative effect.

In our sample, Neuroticism appears to have no effect on earnings. This is in line with findings from other datasets. For example, Piatek and Pinger (2010) show using the German SOEP that Locus of Control, does not influence wages when they control for education.

Note that the effects we just discussed are restricted to be linear, since the factor scores enter the treatment effect analysis only in levels. This restriction might be masking underlying non-linear patterns. However, when we analyze the quadratic terms of the personality factor scores, we find that there is no pervasive evidence for strong nonlinearities. The quadratic terms are not significantly different from zero (regressions are not shown but available upon request).

As a further note, tests of interaction between the effect of personality traits and IQ and education have not indicated any heterogeneity. The interaction terms are never statistically significantly different from zero. The effect of personality traits, in the Terman sample, seems to be working through levels only.

Clearly, personality both drives educational choice and helps explains wage differences within a given education level.

5 Conclusion

This paper estimates the true internal rate of return to education and the present discounted value of education for the high-achieving men of the Terman study without relying on the strong assumptions that are typical in the literature. We establish causality through matching on an unusually extensive list of covariates. The opportunity of analyzing returns to education for the persons at the high end of the IQ distribution, as well as the upper levels of education is unique. We we find that the returns for the Terman men are sizeable.

Personality traits are also shown to have significant and meaningful effects on earnings. Conscientiousness and Extraversion have positive effects on earnings both directly and indirectly through increasing educational attainment. Other traits, such as Agreeableness, have positive indirect effects but negative direct effects. The direct reward to these traits materializes mostly in the prime working years, not during the early part of one's career. IQ, even in this high range, still matters for earnings as well.

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6 Tables and Figures

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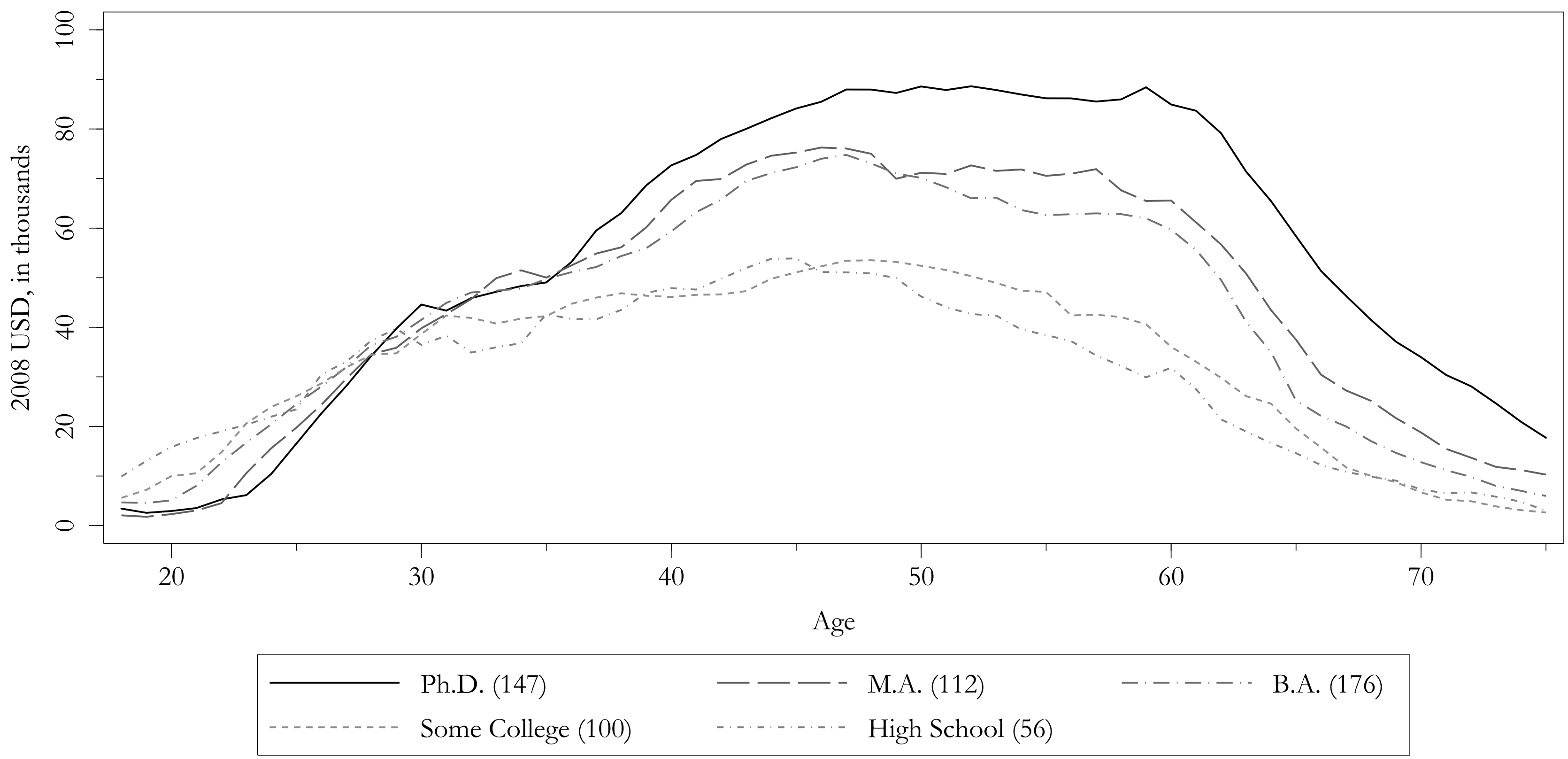
Figure 1: Average Earnings by Education, minus Tuition and After Taxes



Notes: Observation counts are given in parentheses. Earnings are average annual earnings after tax and minus tuition, in 2008 U.S. Dollars, constructed from Terman Data. The tax rates and brackets used are for singles and married persons according to marital status. The tuition cost is applied in full when it occurred, i.e. we do not assume any smoothing out of the payment streams, and we assume graduate students pay full tuition as well. The sample is the same as for the treatment effect computation. The education categories refer to the highest educational level attained in life. See the Web Appendix for information on building the earnings profiles, tuition, and the marriage history, from the raw data.

Table 1: Descriptive Statistics of the Terman Sample used, Part I

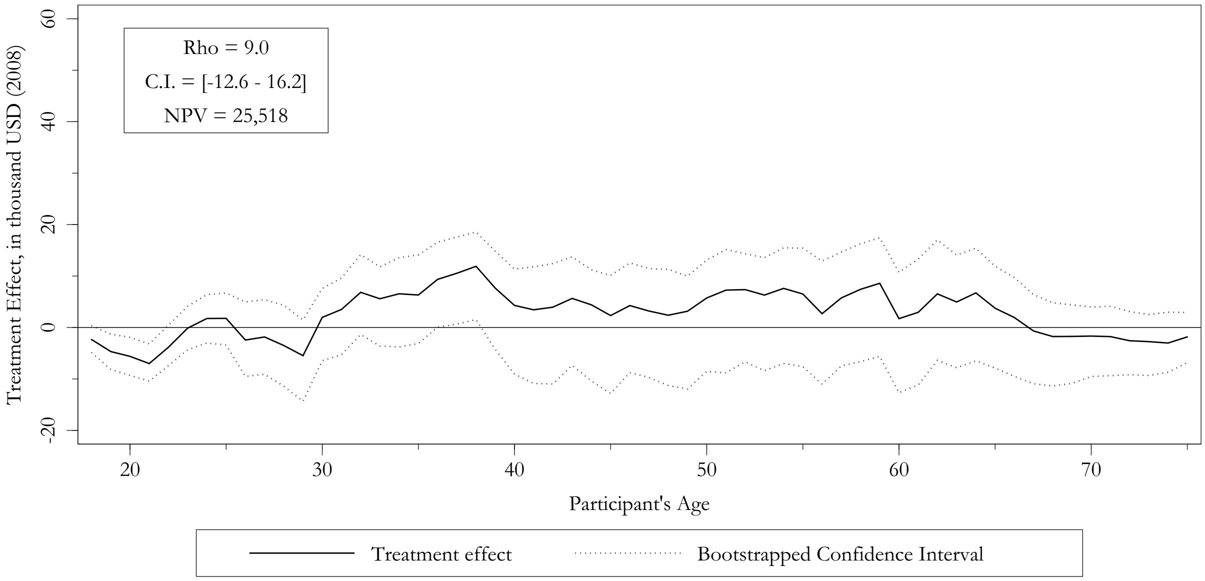
Variable		**Males**	
Education Levels	**Year**	**#Obs**	**%**
High school	1991	56	9.5
Some college	1991	100	16.9
Bachelor's/ some graduate	1991	176	29.8
Master's or equivalent	1991	112	19.0
Ph.D. or equivalent	1991	147	24.9
Basic Information	**Year**	**Mean**	**Std.Dev**
Conscientiousness	1940	0.00	(0.82)
Neuroticism	1940	0.00	(0.61)
Agreeableness	1940	0.00	(0.60)
Extraversion	1922	0.01	(0.68)
Openness	1922	-0.01	(0.83)
IQ normalized	1922	0.00	(0.99)
Terman Group Test	1922	-0.19	(0.37)
Outcomes			
Married at age 30	1934 - 1946	0.73	(0.44)
Married at age 40	1944 - 1956	0.87	(0.34)
Length of life in 1993	1993	72.00	(14.51)
Parental Background			
Father's occupation: clerical or deceased	1922	0.27	(0.44)
Father's occupation: low-skilled	1922	0.17	(0.38)
At least one parent is retired or deceased	1922	0.03	(0.18)
Mother has occupation (not minor)	1922	0.12	(0.32)
Father's age when child was born: >30	1922	0.57	(0.49)
Mother's age when child was born	1922	28.71	(5.42)
Mother's age at birth: <25		0.22	(0.41)
Mother's age at birth: >=35		0.14	(0.35)
Father's highest school grade	1922	10.68	(5.44)
Father's HSG: at most 9 yrs		0.39	(0.49)
Father's HSG: 10-13 years		0.27	(0.44)
Father's HSG: at least 14 yrs		0.34	(0.47)
Mother's highest school grade	1922	10.42	(4.39)
Mother's HSG: at most 4 yrs		0.10	(0.30)
Mother's HSG: 5-11 years		0.39	(0.49)
Mother's HSG: at least 12 yrs		0.51	(0.50)

Table 2: Descriptive Statistics of the Terman Sample used, Part II

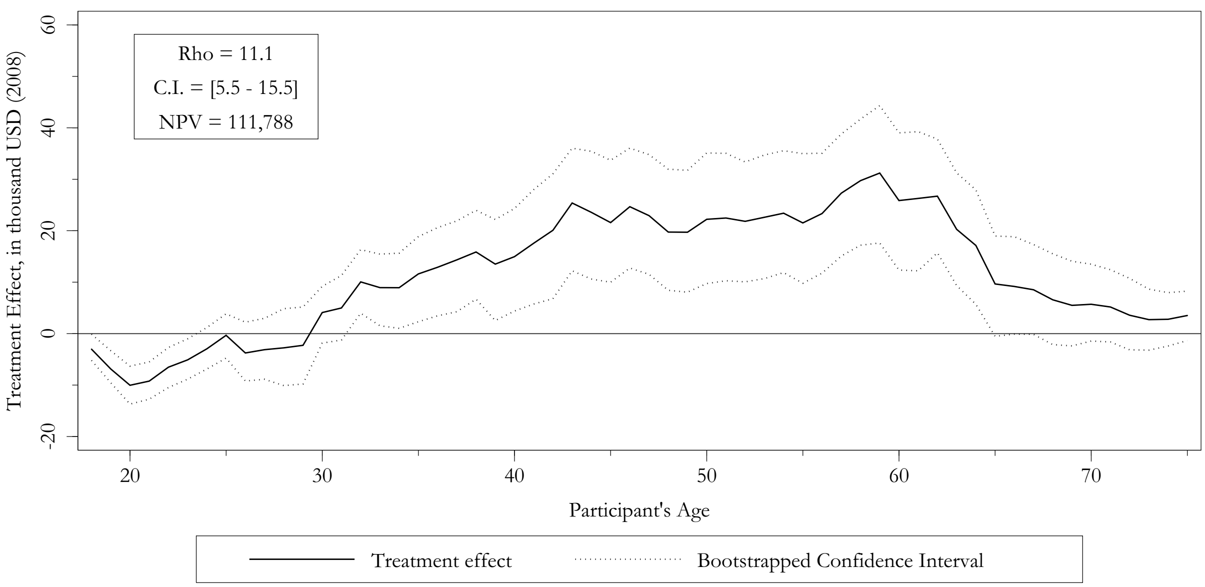
Variable		Males	
Parental Background (continued)	**Year**	**Mean**	**Std.Dev**
Either parent is born in Europe	1922	0.13	(0.34)
Childhood family finances - (very) limited	1950	0.37	(0.48)
Childhood family finances - abundant	1950	0.04	(0.20)
Childhood parental social status - high	1950	0.33	(0.47)
Siblings			
Number of siblings	1940	1.59	(1.61)
No sibling		0.15	(0.36)
2-4 siblings		0.38	(0.49)
5-9 siblings		0.06	(0.24)
Birth order	1940	1.84	(1.27)
Birth order: 2		0.22	(0.41)
Birth order: 3		0.11	(0.32)
Birth order: 4 +		0.20	(0.40)
Early Health			
No breastfeeding	1922	0.09	(0.29)
Birthweight in kilograms	1922	3.80	(0.66)
Sleep is sound	1922	0.97	(0.17)
Cohort Information			
Cohort: 1904-1910		0.22	(0.42)
Cohort: 1911-1915		0.48	(0.50)
WWII combat experience	1945	0.10	(0.30)

Figure 2: Pairwise Treatment Effects on After-Tax Earnings, Males

(a) Some College vs High School



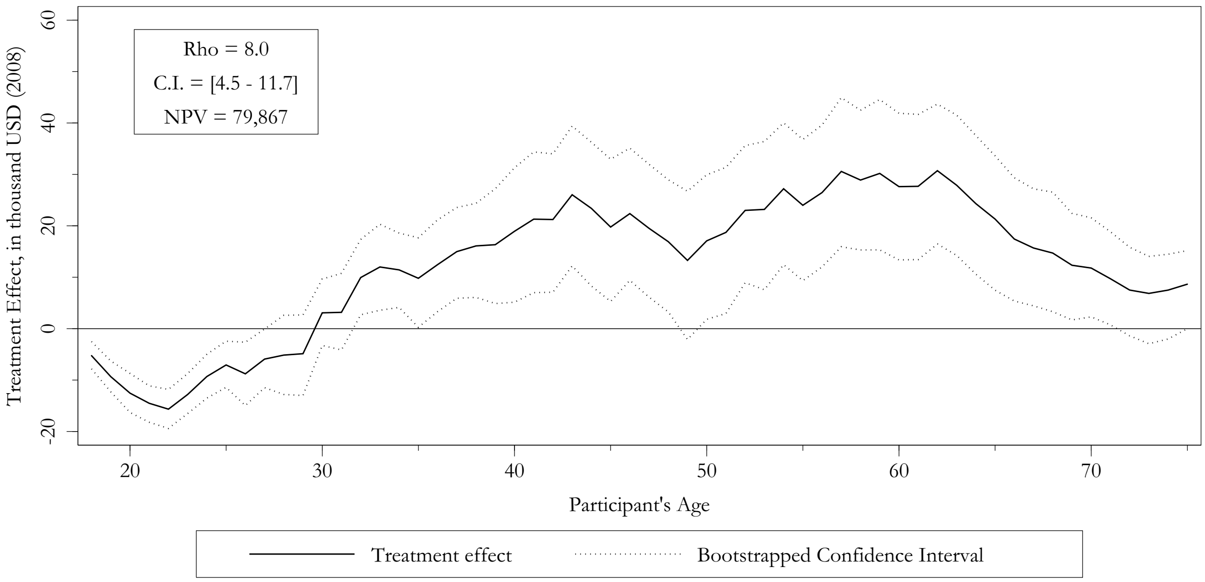
(b) Bachelor's vs High School



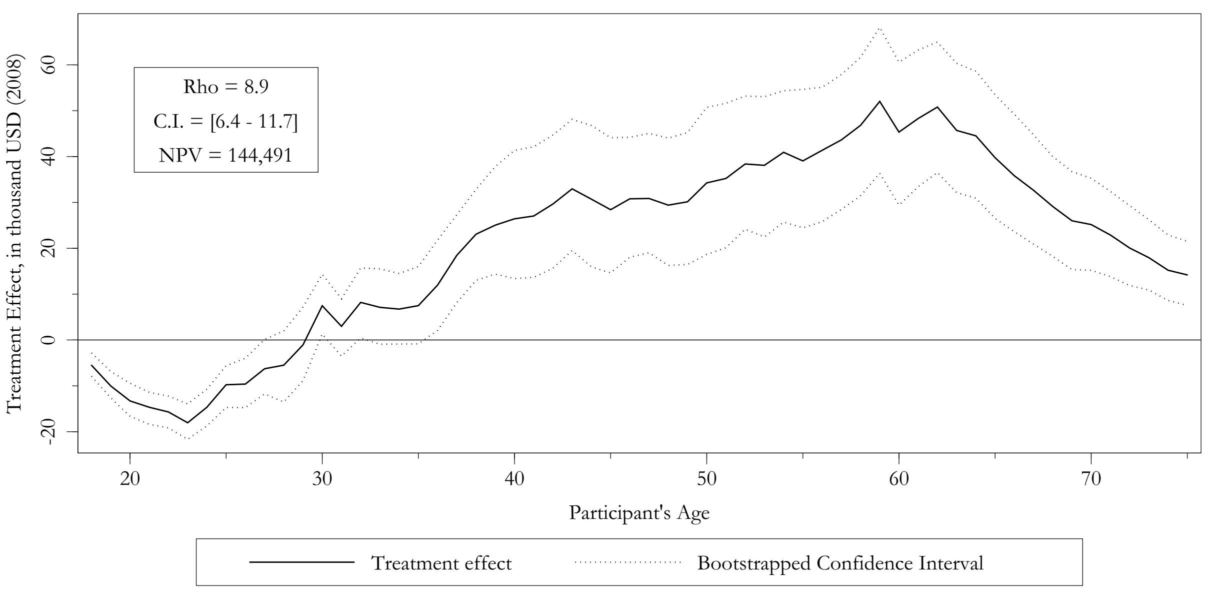
Notes: Treatment effects from the common coefficient model. Dotted lines are the 90% basic bootstrap confidence interval, based on 200 bootstrap draws. Earnings are average annual earnings after tax, in 2008 U.S. Dollars. The tax rates and brackets used are for singles and married persons according to marital status. The tuition cost is applied in full when it occurred, i.e. we do not assume any smoothing out of the payment streams, and we assume graduate tudents pay full tuition as well. The covariates are IQ, factor scores for Conscientiousness, Neuroticism, Agreeableness, Openness, and Extraversion, parental background, family environment, early childhood health and 1922 health information, and controls for WWII and cohort. See Notes to figure **??** or text for more details. See the Web Appendix for information on building the earnings profiles, and the marriage history, from the raw data.

Figure 3: Pairwise Treatment Effects on After-Tax Earnings, Males

(a) Master's vs High School



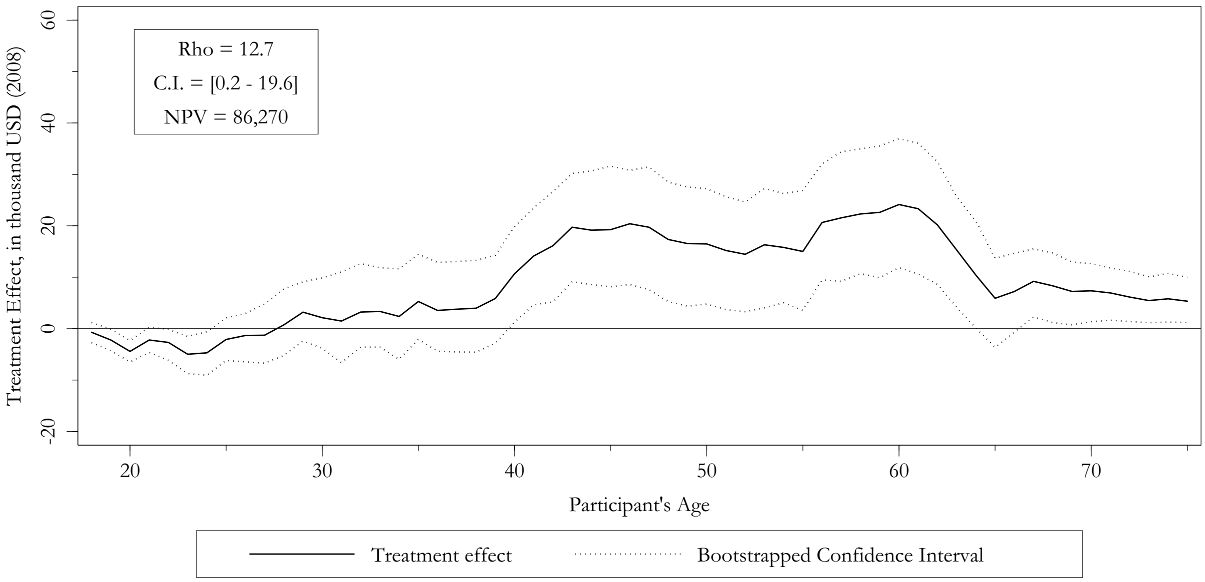
(b) Doctorate vs High School



Notes: See notes to Figure 2.

Figure 4: Pairwise Treatment Effects on After-Tax Earnings, Males

(a) Bachelor's vs Some College

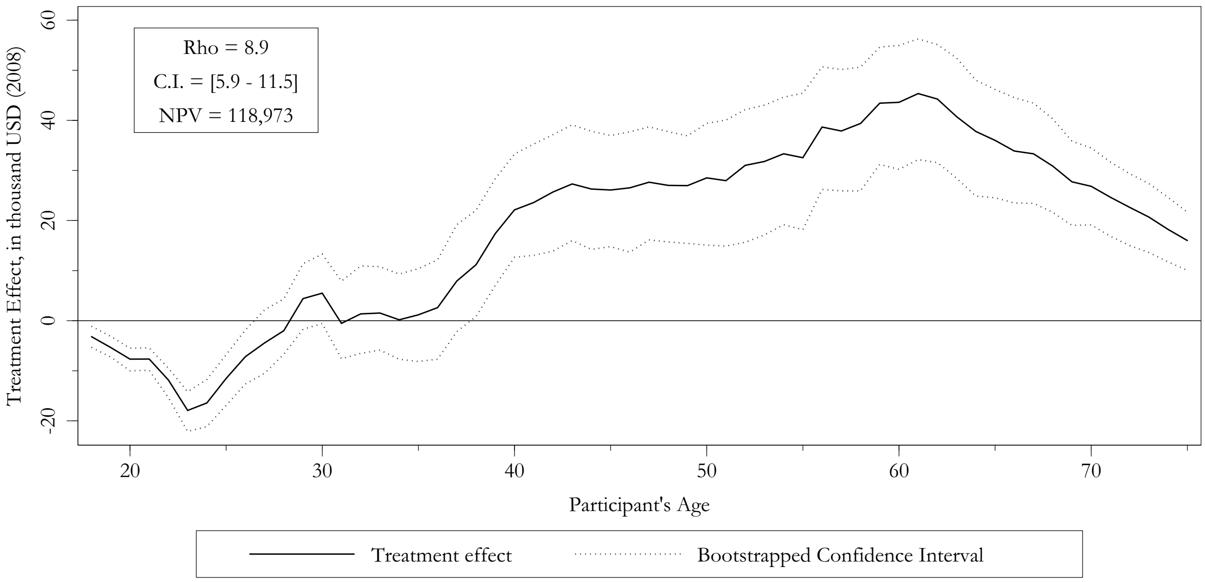


(b) Master's vs Some College

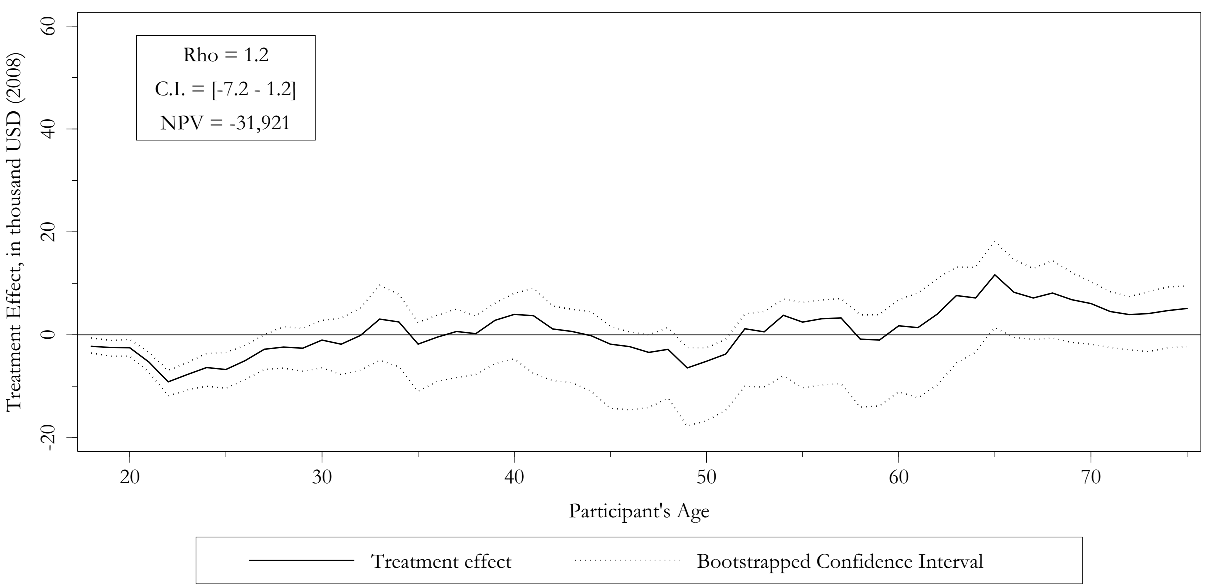
Notes: See notes to Figure 2.

Figure 5: Pairwise Treatment Effects on After-Tax Earnings, Males

(a) Doctorate vs Some College



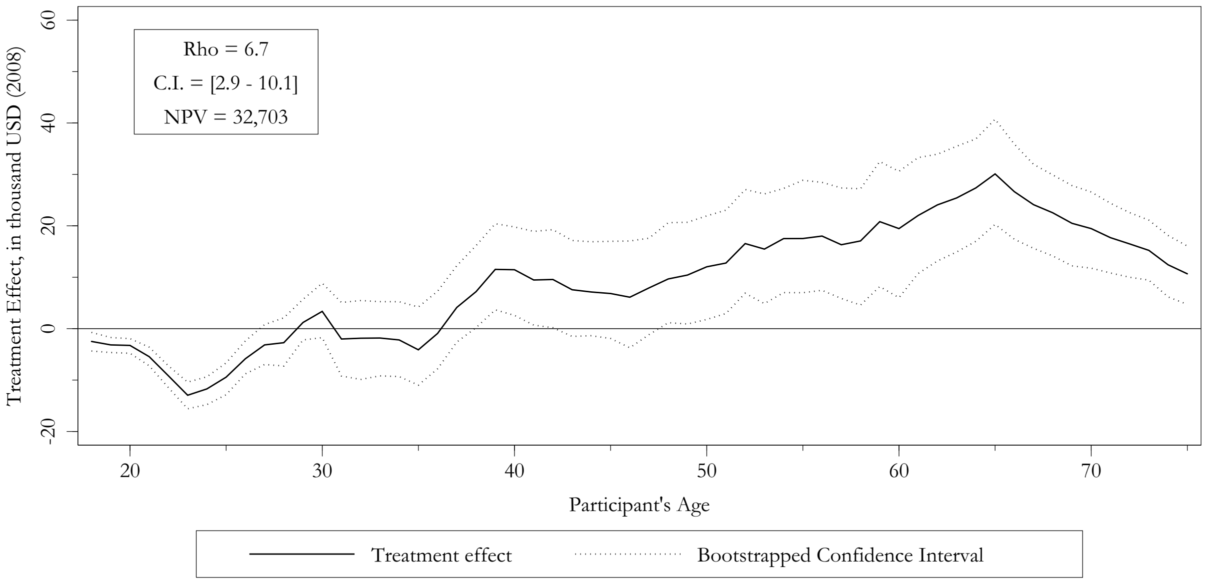
(b) Master's vs Bachelor's



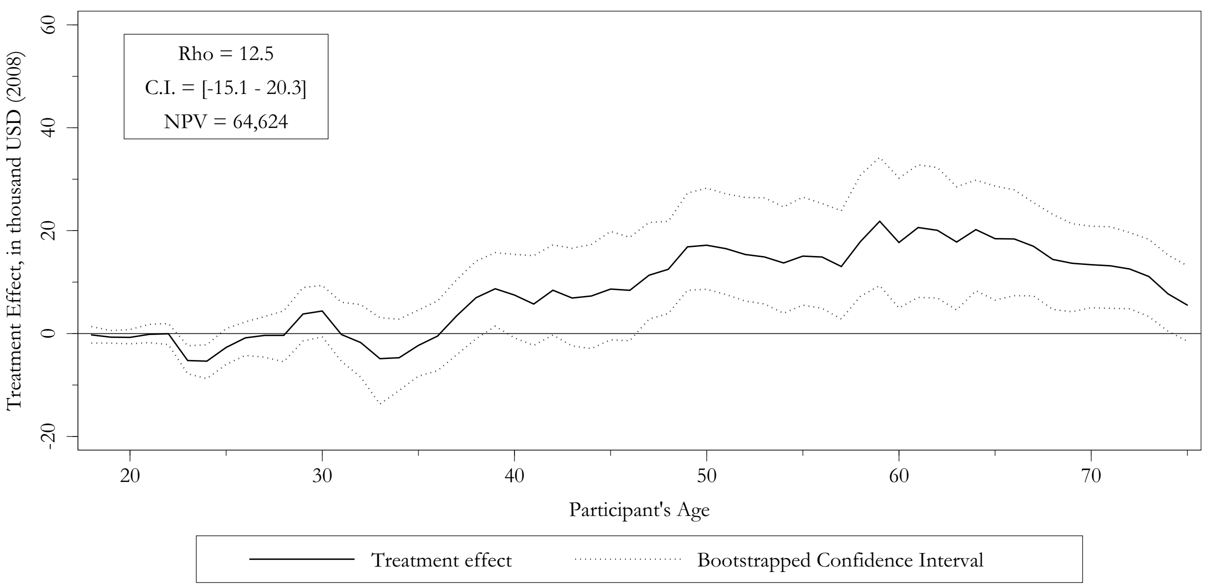
Notes: See notes to Figure 2.

Figure 6: Pairwise Treatment Effects on After-Tax Earnings, Males

(a) Doctorate vs Bachelor's



(b) Doctorate vs Master's



Notes: See notes to Figure 2.

Table 3: Internal Rates of Return and Present Values

	IRR				NPV, r=5%			
	Some Coll.	Bachelor	Master	Ph.D.	Some Coll.	Bachelor	Master	Ph.D.
High School	9.0	11.1	8.0	8.9	25,518	111,788	79,867	144,491
	[-12.6 - 16.2]	[5.5 - 15.5]	[4.5 - 11.7]	[6.4 - 11.7]				
Some College		12.7	7.6	8.9		86,270	54,349	118,973
		[0.2 - 19.6]	[3.4 - 11.6]	[5.9 - 11.5]				
Bachelor			1.2	6.7			-31,921	32,703
			[-7.0 - 4.9]	[3.0 - 10.5]				
Master				12.5				64,624
				[-15.0 - 18.4]				

Notes:
The internal rates of return represent the positive root to the polynomial $\sum_{t=T_{start}}^{T_{end}} \frac{\Delta_t}{(1+\rho)^t} = 0$, where Δ is the difference between two otherwise equal persons with high and low education, the treatment effect of education as in Figures 2 to 4. ρ was found using the mata optimizer in Stata.
The confidence intervals are basic bootstrap confidence intervals, at the 90% level, based on computations of the IRR for each of 200 bootstrap draws.
The discount rate used for the present discounted values is 5%, 3%, and 7% as indicated.
The category of "High School" includes individuals who have attended college but did not obtain a degree. The median length of college for them is 1 year of college, and the mean 1.7. In "Bachelor", persons with some graduate classes are included as well. For them, the median is 1 year of graduate school, and the mean 1.25 The tax rates are for married and single men separately, and we assume tuition was paid in full when college/university was attended (both at the undergraduate and graduate level).

Table 4: Internal Rates of Return and Present Discounted Values, Males, without Personality Traits and IQ

(a) Excluding IQ and Personality from Covariates

	IRR				Percent greater than True IRR			
	Some Coll.	Bachelor	Master	Ph.D.	Some Coll.	Bachelor	Master	Ph.D.
High School	11.0 [0.4 - 20.8]	12.4 [8.0 - 18.7]	9.2 [7.0 - 14.6]	10.1 [8.4 - 14.3]	22%	12%	15%	13%
Some College		13.8 [1.4 - 21.6]	8.4 [4.3 - 12.8]	9.8 [7.0 - 13.4]		9%	11%	10%
Bachelor			1.9 [-6.7 - 3.1]	7.5 [4.6 - 11.6]			58%	12%
Master				14.3 [-34.7 - 23.5]				14%

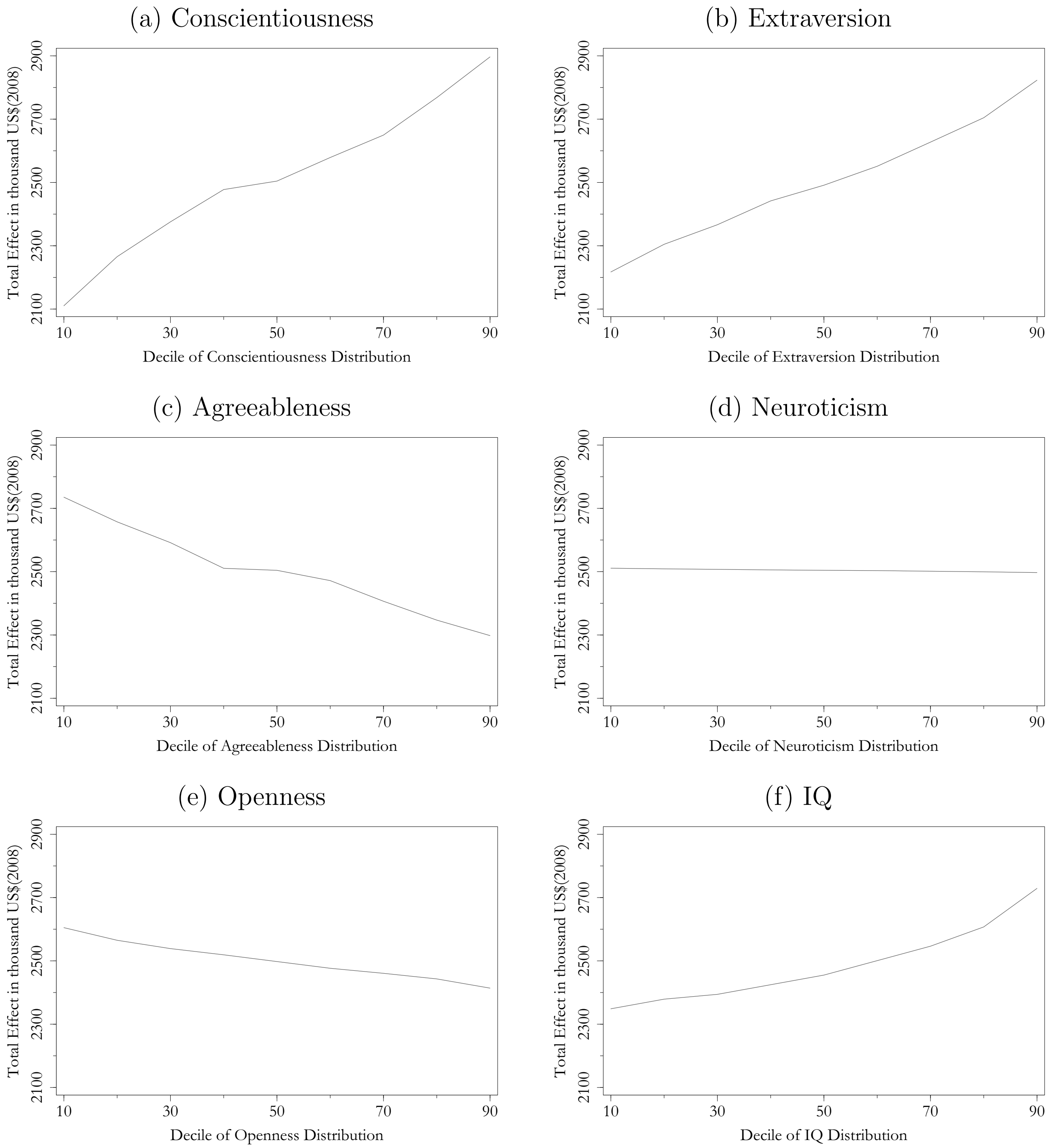
Notes:
See Notes to Table 3 for details about the methodology producing the IRR and NPV.
This table repeats the same estimation as the preferred specification, except for dropping IQ measures and personality factors from the list of covariates.
The bias is computed as (reduced IRR - true IRR)/(true IRR).

Table 5: Determination of Lifetime Earnings

	Total Effect		Total Effect with covariates		Direct Effect, given Education	
	Coefficient	p-Value	Coefficient	p-Value	Coefficient	p-Value
Conscientiousness, 1940/50	412.5	(0.000)	383.8	(0.000)	313.5	(0.000)
Agreeableness, 1940/50	-288.0	(0.013)	-268.9	(0.018)	-274.3	(0.014)
Neuroticism, 1940/50	93.0	(0.419)	-8.5	(0.941)	-30.8	(0.783)
Openness, 1922	-128.0	(0.145)	-86.4	(0.325)	-110.3	(0.199)
Extraversion, 1922	347.5	(0.001)	350.6	(0.001)	354.3	(0.001)
IQ, 1922	201.5	(0.005)	162.3	(0.034)	137.1	(0.067)
High School diploma					-1,260.7	(0.000)
Some College					-1,077.0	(0.000)
College degree					-538.1	(0.003)
Graduate degree					-495.7	(0.015)
Full set of Controls	No		Yes		Yes	
Observations	591		591		591	
Adjusted R-squared	0.061		0.131		0.176	

Notes: The dependent variable is lifetime earnings in thousand US Dollars of the year 2008. It is the sum of all earnings, after tax and tuition, from age 18 to 75 for each Terman male in the estimation sample, undiscounted. For a description of the generation of the lifetime earnings, see the Web Appendix, and Section **??** for the estimation sample.

Figure 7: The Total Effect of Personality and IQ on Lifetime Earnings



Notes: The predictions of lifetime earnings are based on the regression presented in Table 5. Lifetime earnings are the per-person sums of earnings from age 18 to 75, in thousand US-Dollars of the year 2008. They are not discounted. As a baseline, we used means of all covariates, and vary only the factor score in question; thus implicitly holding constant all variables including the other factor scores.

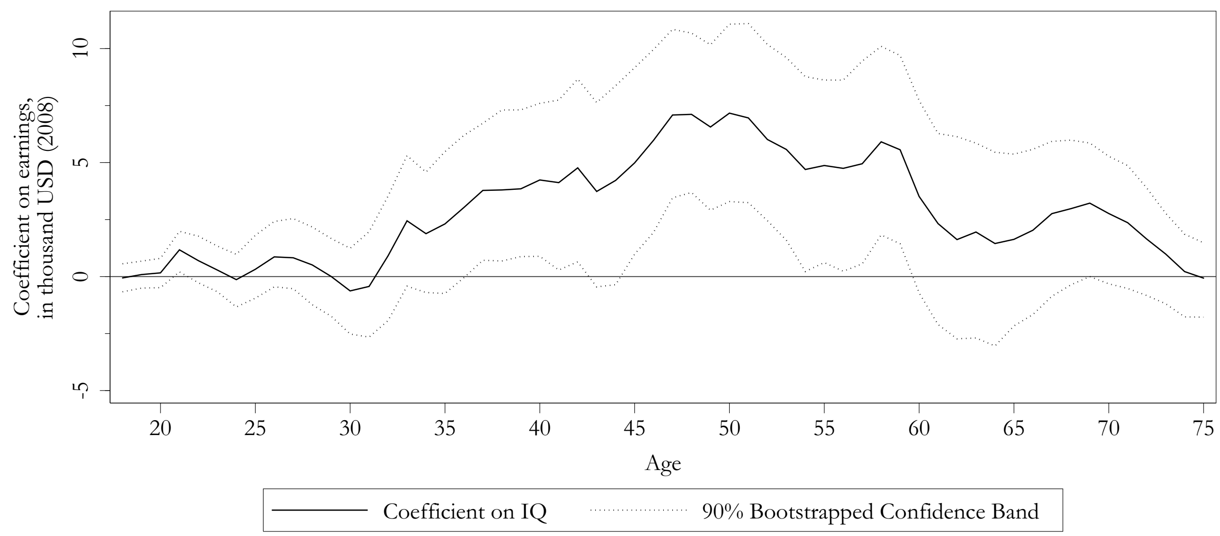
Table 6: Personality Traits in Educational Choice

	Multinomial Logit Estimation							
	Some College		Bachelor		Master		Ph.D.	
IQ	1.51	*(.115)*	**1.64**	***(.045)***	**1.84**	***(.016)***	**1.68**	***(.038)***
Conscientiousness	1.08	*(.713)*	1.21	*(.362)*	1.35	*(.192)*	**1.97**	***(.003)***
Neuroticism	**0.43**	***(.012)***	0.71	*(.254)*	0.71	*(.281)*	0.79	*(.440)*
Openness	0.13	*(.183)*	1.94	*(.656)*	1.11	*(.932)*	0.12	*(.149)*
Openness^2	1.27	*(.289)*	0.90	*(.628)*	0.95	*(.824)*	1.37	*(.160)*
Extraversion	**0.01**	***(.079)***	**0.00**	***(.032)***	**0.00**	***(.015)***	0.09	*(.383)*
Extraversion^2	**2.14**	***(.059)***	**2.35**	***(.027)***	**2.71**	***(.013)***	1.47	*(.334)*
Agreeableness	130.86	*(.174)*	1.46	*(.885)*	2.43	*(.775)*	127.01	*(.143)*
Agreeableness^2	0.51	*(.189)*	0.92	*(.835)*	0.87	*(.764)*	0.50	*(.155)*

Notes:
We present relative risk ratios on the predicted personality factor scores in a multinomial logit estimation. The baseline is high school diploma. The full list of covariates as used in the matching regressions above were also included as regressors. The regression sample is also the same as for the outcome equations (lifetime earnings).

Figure 8: Direct Effect of Personality on Earnings

(a) IQ



(b) Openness

Notes: Graphs show standardized coefficients δ from equation (2.1). The standard deviation in IQ represents 10 IQ points.

Figure 9: Direct Effect of Personality on Earnings

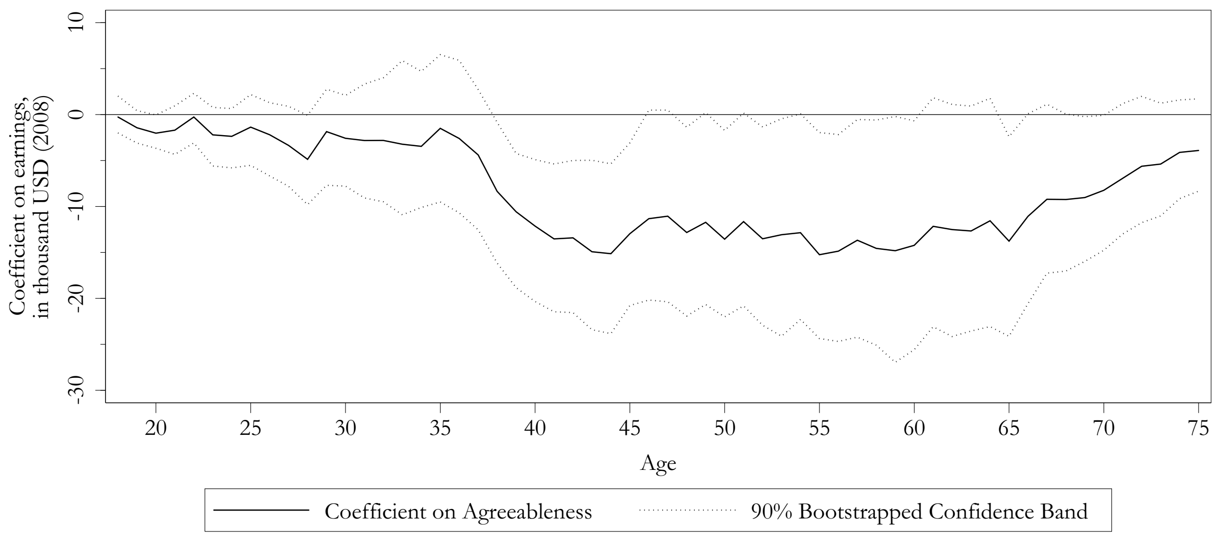
(a) Conscientiousness

(b) Extraversion

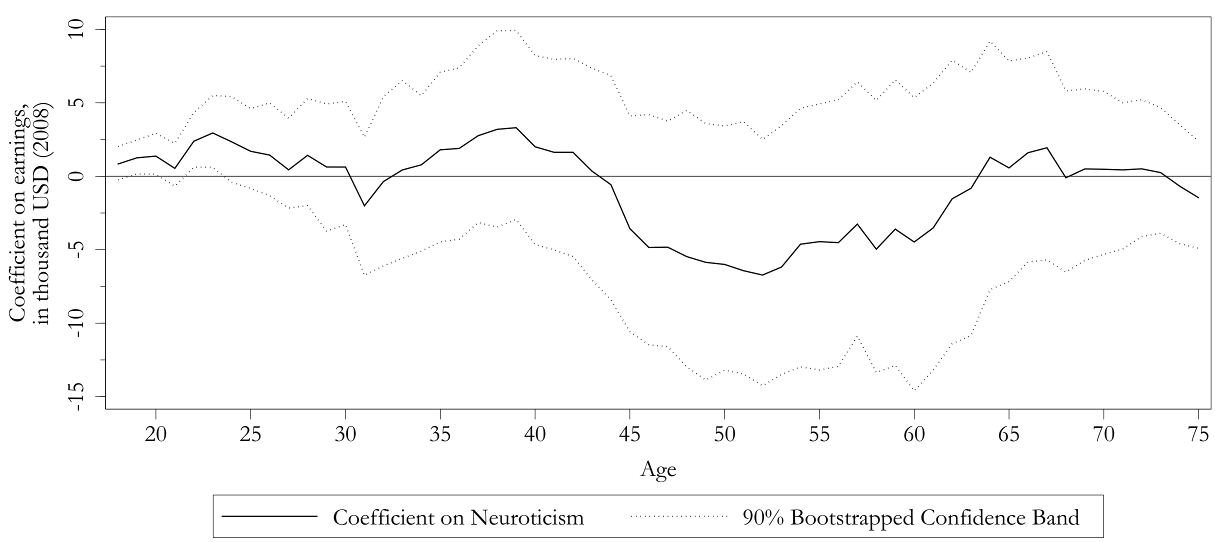
Notes: Graphs show standardized coefficients δ from equation (2.1).

Figure 10: Direct Effect of Personality on Earnings

(a) Agreeableness



(b) Neuroticism



Notes: Graphs show standardized coefficients δ from equation (2.1).