Personality, IQ, and Lifetime Earnings

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Abstract

Talented individuals are seen as drivers of long-term growth, but how do they realize their full potential? In this paper, I show that even in a group of high-IQ men and women, lifetime earnings are substantially influenced by their education and personality traits. I identify a previously undocumented interaction between education and traits in the earnings generation, which results in important heterogeneity of the net present value of education. Personality traits directly affect men's earnings, with effects only developing fully after age 30. These effects play a much larger role for the earnings of more educated men. Personality and IQ also influence earnings indirectly through educational choice. Surprisingly, education and personality skills do not always raise the family earnings of women in this cohort, as women with very high education and IQ are less likely to marry, and thus have less income through their husbands. To identify personality traits, I use a factor model that also serves to correct for prediction error bias, which is often ignored in the literature. This paper complements the literature on investments in education and personality traits by showing that they also have potentially high returns at the high end of the ability distribution.

Key words: lifetime earnings, returns to education, cognitive skills, social skills, personality traits, Big Five, factor analysis, human capital.

JEL codes: J24, I24, J16

Contents

1 Introduction

Talented individuals are seen as drivers of long-term growth (Hughes, 1986; Jones, 2011; Lynn and Vanhanen, 2002; Murphy et al., 1991). But it is not clear why some highly talented individuals realize their potential and others do not. For example, one would expect individuals with IQs above 140, who are in the top 0.5% of the ability distribution, to excel in life, to be over-achievers and to contribute to society by the sheer power of their talent. In a cohort study that follows men and women of this promise, however, we see that while many of them fulfil this expectation, their life outcomes and earnings vary greatly. This paper argues that a substantial amount of this variation can be attributed to differences in education and personality traits. The data for this analysis followed high-ability men and women over their lifetimes, and is called the Terman study.[1]

While a growing literature documents effects of personality traits on earnings, these studies are typically limited to cross-sectional observations, point-in-time measures, or longitudinal datasets with few years of follow-up. Many datasets contain only one or two measures of personality, whereas the Terman study provides measures that map into the well-established comprehensive taxonomy of the Big Five (McCrae and John, 1992). Using the full life-cycle earnings data of the Terman study, I show how personality traits affect earnings differently over the course of a working life. The direct effects of personality traits on earnings are not detectable in the early years of a career—they only develop fully later in a person's working life (after age 30). Furthermore, these effects vary across education levels. Men with post-graduate education benefit from traits such as Conscientiousness or Extraversion more than twice as much than men with a bachelor's degree or less. Most of the existing studies do not allow for this trait-education interaction, and therefore over- or under-estimate the direct effects of personality traits.

Ignoring this heterogeneity is particularly consequential for women. Women might benefit from a given trait if they hold at most a bachelor's degree, but suffer from the same trait when they hold a master's degree or more.

I also analyze how women's family earnings, as opposed to just their own earnings, are differentially affected by personality traits and IQ.[2] Only about half of the women of this cohort are securely attached to the labor force, and many women rely on husbands as bread-winners. Own earnings and husband's earnings react *differently* to personality traits.

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[1]The American psychologist Lewis Terman initiated this study with boys and girls born around 1910. It is the longest prospective cohort study in existence (Friedman et al., 1995), and is described in Terman (1925, 1926, 1930, 1947, 1959).

[2]To obtain family earnings, the full length of the earnings data is supplemented with complete marriage histories, and the corresponding husband's earnings.

Conscientiousness, for example, increases own earnings and decreases spousal earnings for highly educated women.

The finding of strong influences of personality traits on lifetime earnings complements the literature on early childhood interventions, or other programs with a focus on social skill-building activities. Most of these are targeted at disadvantaged, and sometimes low-IQ, populations (examples are Grossman and Tierney, 1998; Heckman et al., 2010, 2013; University of Chicago Crime Lab, 2012). These interventions' attractiveness lies in the greater malleability of social skills than "hard skills" or IQ, which is generally thought fixed after age 10. It is not clear from the literature, however, whether high-IQ children would also benefit from improving these social skills, or whether their life outcomes would even be altered. I show that social skills matter, at least for men, to orders of magnitude that are about half of the impact of education.

I further establish that the effects of intelligence on earnings are still positive even at very high levels of IQ for men. This is not only due to higher educational attainment but also to a direct impact of ability on earnings. For women, in contrast, having a higher IQ results in *lower* lifetime earnings if they are at the top of the educational attainment spectrum.

Personality traits and IQ also have an indirect effect on lifetime earnings, through educational attainment. They might increase the level of education achieved, and thus also increase earnings through positive rates of return to education. In order to identify the rate of return to education, I estimate the causal effect of education on earnings through matching on personality traits, as well as a rich set of background variables that are available in the Terman data. This technique does not rely on instruments and addresses "ability bias" by explicitly accounting for cognitive and "non-cognitive" ability. In computing the internal rates of return, this paper fills in two gaps in the literature on returns to schooling. First, it bypasses the *ad hoc* methods widely used to approximate the rate of return from cross sections of data (Mincer, 1974). By using lifetime earnings histories, it presents *ex-post* estimates of the internal rate of return to schooling. For most pairwise comparisons, the return is substantial. For example, a bachelor's degree over high school diploma yields a return of 12.5% for men. A standard application of the Mincer model produces estimates that are very different from the pairwise returns.

Secondly, this paper explores the rate of return to education for highly able students. Researchers are interested in contrasting rates of return for the "average student" with the "valedictorian." In representative datasets, the number of observations of these high-IQ individuals is so small that any statement about returns at the high end would be unreliable. With the fairly large number of individuals in the Terman study (total of 1528), I can establish that even at the high end of the cognitive spectrum, education has positive returns.

A simple comparison with the 1950 census shows that the returns to a bachelor's degree over high school are slightly higher for the Terman men than the average man (11.4% versus 10.7%). But when the Terman men's earnings are top coded as they would have been in the census, their return decreases to 8.6%.

The cohort studied here was born in the early years of the last century, when women had a fundamentally different role in the labor market and society than women do today (Goldin, 1992). The marriage market determined whether these women benefited from education, or if instead they decreased their family earnings by obtaining post-graduate education. In terms of own earnings, women had low rates of return to education up to a bachelor's degree. Less educated women were unlikely to work, and their skills and education only marginally affected their own earnings. Women with a master's or doctorate degree, however, saw earnings gains that were similar to men's in terms of signs and relative magnitudes.

But education differentially affected family earnings, which are the sum of own earnings and any husband's earnings (which were zero if no husband was present). On the one hand, education increased spousal earnings through assortative mating—the correlation between the spouses' years of education is .36 in the Terman sample. Seventy percent of Terman females with a bachelor's degree married men with a bachelor's degree or more, who had accordingly higher earnings.[3] On the other hand, the most highly educated women were much less likely to be married. This lower propensity to marry represents an additional cost to post-graduate education for women of this cohort.

The paper proceeds in the following way. Section 2 discusses the rich data analyzed in this paper. Section 3 decomposes the effects of psychological traits on total lifetime earnings into the direct and indirect channels. Section 4 breaks down the direct effects by education, and shows results by age. The educational sorting is discussed in Section 5, and the rate of return to education in Section 6. Section 7 concludes.

2   The Terman Survey

The analysis in this paper is based on a survey initiated by the prominent psychologist Lewis Terman to study the life outcomes of high IQ children. The criterion for inclusion in the sample was having a Stanford-Binet IQ score of 140 or higher, which corresponds to approximately 0.5% of the population. These high IQ children were identified through a procedure that canvassed all school grades 1-8 in California in 1921-1922. The Terman sample consists of 856 boys and 672 girls, born around 1910. The cohort was followed until

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[3]The comparable number in the 1940 census is 56-60% (and increases over time), as reported in Mare, 1991 and Pencavel, 1998.

1991, with surveys every 5–10 years.[4] It is the longest prospective cohort study that also has data on earnings.

The Terman data has rich information about its participants. Information is available on their IQs, their personality traits, their early and current health, their background and conditions when growing up, and other aspects of their lives, including marriage, children, and other life events.[5] The educational status and attainment data as well as earnings data is very detailed, allowing me to construct trajectories by age.

The Terman data have been used extensively by psychologists to study health and longevity outcomes in relation to the personality trait of conscientiousness and parental divorce or marriage.[6] Only few economists have worked with the data, and they mainly analyzed family outcomes such as marriage and divorce or fertility (Becker et al., 1977; Michael, 1976; Tomes, 1981). The Terman retirement behavior is analyzed by Hamermesh (1984), and Savelyev (2012) investigates the effects of education and Conscientiousness on longevity. Only the work by Leibowitz (1974) focuses on earnings outcomes, but the longitudinal feature of the data is ignored.

Earnings Histories.   I construct a full lifetime earnings history, as well as education and marriage profiles, for each participant. The earnings measures for computing the rates of return to schooling are annual earnings after tuition, in 2010 U.S. Dollars.[7] Tuition costs are estimated from data on tuition rates at each of the colleges or universities attended by the Terman participants. Tuition is subtracted from earnings at each year that college is attended, at both the undergraduate and graduate level.[8] For inactive workers, as well as for the deceased, earnings are zero. Full life cycle profiles can thus include zeros.

IQ and Personality Measures in the Terman Sample.   IQ is measured at study entry in 1922. The personality traits collected in this early survey are remarkably similar to the modern Big Five taxonomy, even though the measures were collected some 70 years before

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[4]Its attrition rate is less than 10%. Those who dropped out do not differ in terms of income, education, and demographic factors (Sears, 1984), or psychological measures (Friedman et al., 1993).

[5]All survey items are listed in the codebooks Terman and Sears (2002a); Terman et al. (2002a) and Terman and Sears (2002b); Terman et al. (2002b).

[6]Friedman (2000, 2008); Friedman and Martin (2011); Friedman et al. (1995, 1993); Martin et al. (2007, 2002) and Martin et al. (2005); Tucker et al. (1997, 1996, 1999).

[7]The price series used for inflation is the CPI. Web Appendix A, found at http://home.uchicago.edu/~mgensowski/research/Terman/TermanApp.pdf, describes how the earnings profiles were constructed and specifies how tax rates or tuition costs are obtained. The estimations in Section 4 and Section 6 are on pre-tax earnings. For comparability with papers such as Becker (1964) and Heckman et al. (2006), Section C.5 shows all corresponding figures and tables for after-tax earnings. There, tax rates reflect the marital status obtained from the Terman marital histories.

[8]Web Appendix Section C explores different models of subtracting tuition over time, or borrowing.

Table 1: Explanatory Variables Used

	Control Variable	Year	Males Mean	Std.dev	Females Mean	Std.dev
Psych. Traits	IQ	1922	149.4	(10.90)	148.6	(10.34)
	Openness	1922	0.00	(0.85)	0.00	(0.73)
	Conscientiousness	1940	0.00	(0.89)	0.00	(0.71)
	Extraversion	1922	0.00	(0.70)	0.00	(0.82)
	Agreeableness	1940	0.00	(0.66)	0.00	(0.57)
	Neuroticism	1940	0.00	(0.59)	0.00	(0.55)
Parental Background	Father's highest school grade	1922	12.34	(3.61)	12.10	(3.62)
	Mother's highest school grade	1922	11.57	(2.83)	11.69	(2.95)
	Father's occupation: clerical or deceased	1922	26%	(0.44)	24%	(0.43)
	Father's occupation: low-skilled	1922	16%	(0.37)	15%	(0.36)
	At least one parent is retired or deceased	1922	3%	(0.18)	4%	(0.19)
	Mother has occupation (not minor)	1922	11%	(0.32)	10%	(0.30)
	Father's age when child was born	1922	33.42	(8.00)	34.17	(7.67)
	Mother's age when child was born	1922	28.64	(5.39)	29.54	(5.36)
	Either parent is born in Europe	1922	13%	(0.34)	12%	(0.32)
	Childhood family finances (very) limited	1950	38%	(0.49)	38%	(0.49)
	Childhood family finances abundant	1950	4%	(0.20)	6%	(0.23)
	Childhood parental social status - high	1950	35%	(0.48)	33%	(0.47)
Siblings	Number of siblings	1940	1.8	(1.60)	1.8	(1.62)
	Birth order	1940	1.8	(1.27)	2.0	(1.39)
Early Health	No breastfeeding	1922	9%	(0.29)	9%	(0.29)
	Birthweight in kilograms	1922	3.8	(0.65)	3.6	(0.63)
	Sleep is sound	1922	97%	(0.17)	98%	(0.14)
Cohort Info	Cohort: 1904-1910		56%	(0.50)	53%	(0.50)
	Cohort: 1911-1915		44%	(0.50)	47%	(0.50)
	WWII combat experience	1945	10%	(0.30)	0%	(0.07)

the Big Five were codified.[9] The dedicated items for each personality factor were determined with exploratory factor analysis. Web Appendix Section B.2 provides details on the measures and the factor analysis that operationalizes the traits.

Openness and Extraversion are measured in 1922 by ratings from teachers and parents (taking the average). Extraversion is indicated by the subject's "fondness for large groups," "leadership," and "popularity with other children", and Openness is extracted from ratings of the subject's "desire to know," "originality," and "intelligence."[10] The other three traits Conscientiousness, Agreeableness, and Neuroticism are based on self-ratings in 1940. The dedicated items for each are either from a personality inventory,[11] where questions about usual behavior and feelings can be answered "yes," "no," and "?," or self-ratings of personality traits on an 11-point scale. Examples of Conscientiousness items are self-ratings of "How persistent are you in the accomplishment of your ends?" or "In your work do you usually drive yourself steadily?", and an example of an Agreeableness item is "In general, how easy are you to get on with?". Neuroticism is based on questions such as "Are you moody?". The reverse of Neuroticism is called Emotional Stability, so low Neuroticism corresponds to high Emotional Stability.

The personality traits are summarized by factor scores (Jöreskog and Sörbom, 1979; Mulaik, 2010; Thurstone, 1935). Factor scores are predicted using the estimates of a standard linear factor model, using the Bartlett method (Bartlett, 1937; Thomson, 1938). Even though the Terman survey is very selective in terms of IQ, it is not selective in terms of personality, as Martin and Friedman (2000) show. Generally, IQ and personality are only weakly correlated (see Dauber and Benbow, 1990; Eysenck, 1993). The only trait that is moderately positively correlated with IQ is Openness to experience.

Education and Background Variables. The covariates that are used as control variables include father's and mother's backgrounds (education, occupation, social status, region

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[9]See Goldberg (1993). The Big Five traits are Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism (OCEAN). While the traits from the Terman data are conceptually very close to the Big Five personality traits, they are not measured using the same inventory. Martin and Friedman (2000) have established that the personality factors based on the Terman questionnaires correspond closely to the analogous Big Five traits. The correlations with scores on the NEO PI-R are high.

[10]Since "intelligence" is a facet of Openness, it might seem as if Openness and IQ measure the same underlying trait (see the discussion in Almlund et al., 2011). Note that the IQ test is a direct measure 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 generate 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 correlated with IQ. The correlation coefficient is $r = .2$ in the Terman sample, significantly different from zero. The other four personality traits are not significantly correlated with IQ in the Terman data.

[11]The Bernreuter scale is described in Terman et al. (2002a).

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). Descriptive statistics of these variables are given in Table 1.

Sample. The sample used to conduct the analysis does not include the youngest and oldest participants, since their selection into the sample was non-standard.[12] Only respondents with valid education information are included. Non-Caucasian children and those with rare genetic diseases are excluded. In order to have full earnings histories from age 18 to 75, only individuals with 10 or fewer years of missing earnings information are retained in the sample. The estimation sample thus consists of 595 men and 422 women.

3 The Effects of Psychological Traits on Lifetime Earnings

IQ and personality traits influence the lifetime earnings of men and women in the Terman sample. Over a lifetime, how much more will more conscientious men earn? Scoring one standard deviation higher will lead to about 18% higher lifetime earnings. But different channels might be responsible for this effect. Personality traits could influence wages directly in the marketplace, through pricing of the traits in a hedonic model. Alternatively, it is known that personality traits influence educational attainment—if there is a positive return to education, traits might thus have an indirect effect on lifetime earnings through educational attainment. This section estimates the total marginal effects of traits on the sum of lifetime earnings and decomposes them into direct and indirect effects.

3.1 Estimation Procedure

All effects of education and personality traits on earnings are identified using a "selection on observables" or "matching" assumption (Heckman and Robb, 1985), based on a full set of covariates. The exact link to the standard Roy model of counterfactuals is presented in Section B.1. The specific implementation of this assumption here is Ordinary Least

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[12]While most students were identified through the canvassing of schools, few other students were included in the sample because the researchers were made aware of these intelligent children through other means—for example, by their siblings (Terman, 1925). See Web Appendix A.6 for a detailed description of the estimation sample and how it differs from the complete Terman sample.

Squares,[13] as in the following estimation with a linear specification for earnings at age t:

$$Y_t = \theta \sum_{j=1}^{J} D_j \delta_{j,t} + \sum_{j=1}^{J} D_j \kappa_{j,t} + X_t \beta_t + \rho_t \qquad t = 1, \ldots, T; j = 1, \ldots, J. \qquad (1)$$

θ is a vector of traits (IQ and personality factors), $\delta_{j,t}$ the corresponding coefficients by schooling level j, and D_j an indicator matrix of the same dimension as $\delta_{j,t}$. $\kappa_{t,j}$ is the average treatment effect of schooling, or the causal effect of schooling given the matching assumption. X_t is a vector of background variables with coefficients β_t, and ρ_t is a mean-zero error term. Equation (1) is estimated separately for men and women.

Since the factor scores for personality traits are estimated on the basis of factor model estimates, their predicted values contain prediction uncertainty and the variance of these scores is higher than of the true factors. Simply including factor scores in a least squares regression leads to attenuation bias in the coefficients. This bias is usually ignored by economists using predicted factor scores, which might explain frequent insignificant effects of these factor scores. In this paper, I correct for this estimation error with the method described by Croon (2002). This method was developed for the simple model where factor scores enter in levels only. Thus, the bias correction has to be expanded to account for the interaction terms between the predicted factor scores and education in Eq. (1). Section B.3 in the Appendix provides the details of how I perform this adjustment. It is standard practice to bootstrap the standard errors or estimate them with other Monte Carlo methods (Bolck et al., 2004), because regular standard errors do not take account of the prediction variance and the fact that the measurement system is estimated. All standard errors presented are bootstrapped non-parametrically and all estimates, unless otherwise noted, condition on personality traits (using extracted factors), IQ and family background variables.

As described in Section 2, the measures of personality traits are obtained when the Terman participants were around 12 - 30 years old. While levels of psychological traits change systematically with maturation, personality throughout adulthood is very stable over time in terms of rank order. As numerous studies have shown, the rank order correlation of traits within one person over very long time spans is remarkably high,[14] and even from adolescence to adulthood there is "more stability than change" (Roberts et al., 2001). Judge et al. (1999) show that the correlations of Big Five traits with adult income and occupational status are practically identical between childhood personality measures and measures taken in adult-

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[13]The results presented here do not depend on the assumption of linearity — other models, including a nonparametric one, yield the same effects of education on earnings. The description of these, and a comparison of the results, is in Web Appendix Section C.8.

[14]See Costa and McCrae (1994); Leon et al. (1979); Roberts and DelVecchio (2000); Roberts et al. (2006); Robins et al. (2001).

hood. Thus, the present identification of effects of personality traits relies on the assumption that the rank in traits which are measured relatively early in the Terman participants' lives are representative of what their rank will be later on. At the same time, this stability does not extend to childhood. On the contrary, personality has been shown to be more malleable than IQ throughout childhood. In this sense, this paper exploits the duality of changeability and stability of traits at the same time.

As a first overview, the effects of personality traits on total lifetime earnings, defined as $Y_i^T = \sum_{t=18}^{75} Y_{it}$, are analyzed. Based on an equation similar to Eq. (1), define conditional average lifetime earnings as

$$E\left[Y^T|\theta, X_t\right] = \theta \sum_{j=1}^{J} \delta_{j,T} E\left[D_j|\theta, X\right] + \sum_{j=1}^{J} \kappa_{j,T} E\left[D_j|\theta, X\right] + X\beta_T \tag{2}$$

3.2 Decomposing the Effect of Personality and IQ on Total Lifetime Earnings

The marginal average effect of trait θ_k can be decomposed into a direct effect and two indirect effects:

$$\frac{\partial E\left[Y^T|\theta, X_t\right]}{\partial \theta_k} = \underbrace{\sum_{j=1}^{J} \delta_{k,j,T} E\left[D_j|\theta, X\right]}_{direct} + \underbrace{\theta \sum_{j=1}^{J} \delta_{j,T} \frac{\partial E\left[D_j|\theta, X\right]}{\partial \theta_k}}_{indirect(alt.direct)} + \underbrace{\sum_{j=1}^{J} \kappa_{j,T} \frac{\partial E\left[D_j|\theta, X\right]}{\partial \theta_k}}_{indirect(education)} \tag{3}$$

The magnitude of the direct effect of traits depends on educational attainment, since the specification in (1) allows for heterogeneous effects. The indirect effects both arise because trait θ_k alters educational attainment. At a different educational attainment, the direct effects of all personality traits are altered (indirect(alt.direct)), and naturally there is a different return to education (indirect(education)). Educational choice, and thus $E\left[D_j|\theta, X\right]$ is estimated with an ordered probit for the decomposition of direct and indirect effects.

Figure 1 presents the decomposition of these marginal effects of personality and IQ on total lifetime earnings of men and women in the Terman sample. Personality traits and IQ clearly play a large role in determining lifetime earnings of males (first row). *Ceteris paribus*, lifetime earnings are higher if the men are more conscientious and extraverted, and if they are less agreeable. Lifetime earnings are also increasing in IQ.

The decomposition reveals two facts. First, the direct effect of traits on earnings outweighs the indirect effects through education. This implies that researchers who find associations between traits and earnings should focus on interpretations that relate traits directly

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Figure 1: Decomposition of Marginal Effects of Psychological Traits on Lifetime Earnings

Notes: Stacked marginal effects showing how much a one-standard deviation increase in each personality trait influences total lifetime earnings (results from estimation equation Eq. (3), evaluated at median values of all covariates and personality traits). The dependent variable is total lifetime earnings in thousand US Dollars from age 18 to 75, after tuition. One indirect effect is not shown, indirect(alt.direct) in Eq. (3), because the traits are centered around zero, making this particular indirect effect zero as well.

to earnings rather than to education. It also raises the question of why the indirect effects are relatively smaller. It might be because the marginal effects of the traits on educational attainment are small, or because returns to schooling are small. Sections 5 and 6 will show that the returns to schooling are substantial, but that some traits have a limited influence on educational attainment, such as Extraversion in men. Second, direct and indirect effects do not have to be of the same sign. As demonstrated by Openness to experience and Agreeableness, personality traits that increase educational attainment might not be rewarded in the marketplace directly.

Women's own lifetime earnings (second row) are affected differentially by traits — except for Conscientiousness, which has similarly positive direct and indirect effects. For other traits, women do not see large direct effects. Instead, most traits have negative indirect effects. The family earnings of women (third row) are only significantly related to Conscientiousness and Extraversion, which have large positive direct effects. Generally, the effects of personality traits on life-time earnings are much smaller for women, even accounting for their spousal earnings.

4   The Direct Effects of Personality Traits and IQ on Earnings

Given the importance of direct effects on lifetime earnings, we should ask how these direct effects vary by educational attainment (Section 4.1). The direct effects of traits on women's family earnings are decomposed into the direct effect on own earnings and on husbands' earnings in Section 4.2. When do gains or losses occur? Section 4.3 shows how the effects vary over the life cycle for men. The largest effects (both positive and negative) occur later in the working life.

4.1   Effects on Lifetime Earnings by Education for Men

Table 2 shows the direct effects of traits on total lifetime earnings for two different levels of education j, "Bachelor's or less" and "Master's or more." These are the $\delta_{j,T}$ of equation (2). The bottom half of Table 2 tests whether the effects are in fact equal, or $\delta_{j,T} - \delta_{k,T} = 0$. Since many of the differences are statistically significant, it highlights the importance of accounting for heterogeneous effects of the personality traits by educational attainment.

For men, the direct effect of IQ is positive, but when estimated separately by education level, not statistically significant.[15] Conscientiousness and Extraversion are strongly associ-

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[15]When the $\delta_{j,T}$ are estimated as δ_T only, the effect is significant (not reported). Therefore, the lifetime

Table 2: The Direct Effects of Personality and IQ on Lifetime Earnings by Education

	Men	Women		
	(1)	(2)	(3)	(4)
Direct Coefficients	Own Earn.	Own Earn.	Husband's	Family
IQ:				
- BA or less	158.9 (0.24)	1.2 (0.48)	66.3 (0.25)	65.0 (0.25)
- MA or more	162.1 (0.15)	-9.7 (0.48)	-499.1*** (0.01)	-501.9** (0.01)
Openness:				
- BA or less	-120.4 (0.27)	16.6 (0.47)	-385.5* (0.06)	-387.4** (0.04)
- MA or more	-221.9 (0.20)	72.5 (0.35)	539.1* (0.07)	557.9* (0.07)
Conscientiousness				
- BA or less	233.3* (0.05)	66.8 (0.11)	250.7 (0.13)	310.2** (0.03)
- MA or more	571.6*** (0.00)	297.9** (0.03)	-285.8 (0.22)	-12.8 (0.47)
Extraversion				
- BA or less	266.9** (0.04)	-9.6 (0.46)	450.9** (0.05)	479.9** (0.01)
- MA or more	694.4*** (0.00)	-123.9 (0.25)	-289.5 (0.16)	-340.0* (0.09)
Agreeableness				
- BA or less	-184.4 (0.17)	-51.3 (0.27)	316.1* (0.09)	246.8 (0.12)
- MA or more	-420.8*** (0.01)	23.5 (0.38)	-114.5 (0.33)	-125.0 (0.33)
Neuroticism				
- BA or less	-160.9* (0.08)	-38.7 (0.23)	103.7 (0.28)	51.7 (0.36)
- MA or more	133.1 (0.23)	-161.7 (0.11)	16.4 (0.46)	-111.4 (0.34)

	Men	Women		
	(1)	(2)	(3)	(4)
Difference: MA - BA	Own Earn.	Own Earn.	Husband's	Family
IQ	3.2 (0.42)	-10.9 (0.46)	-565.4** (0.01)	-566.9*** (0.00)
Openness	-71.4 (0.37)	43.7 (0.37)	722.7* (0.05)	738.8** (0.02)
Conscientiousness	259.8* (0.06)	192.7* (0.07)	-447.2 (0.12)	-269.2 (0.19)
Extraversion	427.5** (0.01)	-114.3 (0.29)	-740.3** (0.04)	-819.8** (0.01)
Agreeableness	-307.8 (0.17)	89.8 (0.34)	-516.7 (0.15)	-446.0 (0.21)
Neuroticism	417.8* (0.08)	-157.4 (0.18)	-111.7 (0.39)	-208.7 (0.28)
Mean Life Earn.	3390.5	696.2	2098.1	2807.3
Observations	595	422	422	422

Notes: The dependent variable is total lifetime earnings in thousand USD, ages 18 to 75. The top table shows standardized coefficients δ_j from Eq. (1). The bottom table shows the difference between the coefficients by education level of the top half. The p-values in parentheses, $^*p < .1,^{**}p < .05,^{***}p < .01$, correspond to the bootstrap estimated probability of observing an absolutely larger value of the test statistic under a Null hypothesis of no effect on average.

ated with higher earnings—but the reward to being more conscientious and extraverted is greater for more highly educated men. This difference is statistically significant with p-values of 6% and 1%, respectively.

Extraversion should have a positive effect on earnings because this trait has been found to increase job performance, particularly in management and sales occupations (Barrick and Mount, 1991). Extraversion showed positive effects on wages in Heineck and Anger (2010); Judge et al. (1999) and O'Connell and Sheikh (2011). Nyhus and Pons (2005) find an interaction between Extraversion and education, similar to what Table 2 shows: more positive effects for more highly educated men. Using a cross-section of Dutch households, they estimate a Mincer-regression of wages that includes personality and education interactions. For men, Extraversion and "Autonomy" (a personality factor not measured in Terman) are the only personality traits with differential effects by education. The base-level effect of Extraversion, however, is *negative* for men in the low education category (which roughly corresponds to secondary education and vocational training at most). Heineck (2007) showed insignificant results for Extraversion.

Conscientiousness has consistently been found to be associated with better job performance (Barrick and Mount, 1991; Mount et al., 1998; Salgado, 1997). With job performance indicating productivity on the job, we should expect a positive association between Conscientiousness and wages as well. Indeed, this is shown by Heineck (2007); Heineck and Anger (2010); Judge et al. (1999); O'Connell and Sheikh (2011). Only in Nyhus and Pons (2005) does Conscientiousness not have a significant effect on wages.

More agreeable men earn less if they have a Master's or a doctorate degree. This might be surprising when we think about which personality traits are likely to be valued by employers because they align incentives between them and their employees, such as Bowles et al. (2001). More agreeable employees are less antagonistic and more likely to act towards others' interests instead of their own, therefore they are more likely to cooperate with the employer. They also perform better in teamwork situations (Barrick and Mount, 1991; Mount et al., 1998; Salgado, 1997; Tett et al., 1991). However, these workers might not be rewarded for their agreeableness because they are also less aggressive in wage bargaining. It is also possible that agreeable individuals select into lower-paying occupations, or that they have lower manipulative power, or 'Machiavellian intelligence' (Turner and Martinez (1977), pointed out by Nyhus and Pons, 2005). The finding of lower earnings for less antagonistic men is not unique to the cohort studied here, or to high-IQ men: Wage penalties to agreeableness have previously been found by Müller and Plug (2006) for the Wisconsin Longitudinal Study,[16]

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effect of IQ on earnings is driven both by higher educational attainment associated with higher IQ, and also through a direct impact on earnings. IQ impacts earnings in a similar fashion across education levels.

[16]Interestingly, these authors also show that Conscientiousness is not significantly different from zero for

Boudreau et al. (2001) for a sample of executives from the US and EU in 1995/1996, Heineck (2007) for a 2005 UK sample (BHPS), O'Connell and Sheikh (2011) for a 2008 UK sample (NCDS), and Heineck and Anger (2010) using the representative German panel data GSOEP in the years 1991-2006.

Neuroticism is expected to have a negative effect on earning. Emotional stability, the reverse of Neuroticism, has a positive association with wages in Boudreau et al. (2001); Heineck (2007); Judge et al. (1999); Müller and Plug (2006); Nyhus and Pons (2005); O'Connell and Sheikh (2011). More secure, independent, and less anxious workers have better job performance (Barrick and Mount, 1991; Mount et al., 1998; Salgado, 1997; Tett et al., 1991). There are well-known results for self-esteem (measured with the Rosenberg scale in the NLSY 1979), and "evidence suggests that self-esteem and locus of control indicate the same factor as Neuroticism" (Judge et al., 1998). Goldsmith et al. (1997); Murnane et al. (2001) find positive effects of self-esteem on wages at age 27-28 in the NLSY 79.[17] This is confirmed by lifetime earnings effects in the Terman data, but only for men with at most a bachelor's degree. Men with low emotional stability (high scores of Neuroticism) are *not* punished when they are highly educated. The point estimate is even positive, which would indicate a benefit from Neuroticism at that education level. While the estimate is not significant, the positive difference to less educated men is significant. Nyhus and Pons (2005), the only study that explicitly allows for interaction effects with education, also find that men with a university education benefit significantly less from emotional stability than men with medium or low education.

Openness to Experience is not statistically significant in the Terman data. Previous studies also show mixed results for this trait: It increases earnings in Müller and Plug (2006) and O'Connell and Sheikh (2011), even controlling for cognitive ability, but is negative in Heineck and Anger (2010) and insignificant in Heineck (2007). Because of its positive correlation with IQ, Openness is often found to have a positive effect on earnings in analyses that do not control for IQ. These results are upwardly biased. Controlling for IQ, Openness does not have a clear effect on earnings in the Terman study. While in Terman, the IQ-Education interaction is not significant, Hause (1972) establishes significant interactions between schooling and AFQT or ability in two different data sets (NBER-Thorndike, and Project Talent), of which at least the latter is a representative sample. In Terman's very restricted IQ range, this can not be identified.

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men in the Wisconsin Longitudinal Study; whereas it is clearly so in Terman.

[17]Goldsmith et al. (1997) cite evidence that workers with higher self-esteem are more productive. Heckman et al. (2006) average the Rosenberg scale with the Rotter Internal-External Locus of Control Scale. This "noncognitive measure" has strong wage effects for both men and women at age 30, holding education constant (page 418).

What could explain the finding that traits have larger effects on earnings for more educated men? First, it could reflect true human capital differences. Social skills are inputs into the human capital production function just as cognitive skills are. Without participation in class, interactions with teachers and peers, dedication and preparation, little will be learned at school. Thus, the more conscientious and extraverted men acquire more human capital in school, and thus have a higher stock of human capital at the end than the less conscientious and extraverted. This difference in human capital might be reflected in the additional positive effect of these traits on wages.

The second reason why some traits would be rewarded more highly in more educated men is related to occupational differences by schooling classes. Choice sets from which individuals choose their occupations will differ by education. It is thus possible that more highly educated men are better able to choose occupations that reward their traits than less educated men. Take executives as an example. The prevalence of executive positions is much higher in the higher education group. Conscientiousness, Extraversion, and Emotional Stability are significantly associated with "executive strengths" (Holland et al., 1993), and they are positively correlated with leader emergence and leader effectiveness (Judge et al., 2002). Thus, if education opens access to these occupations that would reward the conscientious and extraverted more, there is a higher trait reward in high education groups.

Could the wage effect differentials be explained away by differential occupational sorting? Due to the sample size in Terman, it is difficult to control for occupations in a meaningful way. But evidence from other studies shows that effects of non-cognitive skills on earnings persist even when occupation dummies are included. For example, in Kuhn and Weinberger (2002), leadership skills have positive wage effects even "within very narrowly-defined occupational groups."

4.2   Effects on Lifetime Earnings by Education for Women

For women, accounting for the heterogeneity of the direct effects of personality traits is even more important than for men. In many cases, the effects have opposite signs. Analyses that ignore these interactions over- or under-state the effects of these traits when considering the average impacts only. Furthermore, one needs to distinguish between own earnings and family earnings (combined with husbands' earnings), because the effects of psychological traits are different between these two earnings sources.

As column (2) of Table 2 shows, women only benefit directly (in terms of **own earnings**) from the trait of Conscientiousness, and only if they are highly educated. In this sense, only the highly educated women receive rent on their human capital as the men of this sample

do. They are not pulling equal to men, however, since the absolute magnitude of the effect of Conscientiousness for women with post-graduate education is closer to the effect for men with a bachelor's degree or less. In the generation immediately following the Terman women, Conscientiousness is generally associated with higher earnings, as Müller and Plug (2006) show for women born around 1940.

More conscientious women do *not* benefit in terms of **family earnings**, because Conscientiousness has a negative effect on husband's earnings (column 4 of Table 2). For women with a bachelor's degree, Conscientiousness does lead to higher family earnings overall, mainly through higher husband's earnings (column 3). But we do not know a priori whether this means that these conscientious women marry more frequently or rather higher earning husbands (or both). Formally, family earnings Y^F consist of the sum of a woman's own earnings, Y^W, and her husband's earnings Y^H, if a husband is present (year subscripts omitted for readability). Her own earnings are defined by Eq. (1). Assume that her husband's earnings, conditional on being married, are governed by a similar process, as a function of X, θ, and schooling s :

$$Y^H(X, \theta, s) = \theta \sum_{j=1}^{J} D_j(X, \theta) \widetilde{\delta}_j + \sum_{j=1}^{J} D_j \widetilde{\kappa}_j + X\widetilde{\beta} + \varepsilon$$

Let the indicator for being married be D_M, and allow the probability of being married to depend on covariates X, psychological traits θ, and education level s. Thus

$$E[D_M|X, \theta] = \sum_{j=1}^{J} E[D_j|X, \theta] E[D_M|X, \theta, s = j]$$

$$
\begin{aligned}
E[Y^F|X, \theta] &= E[Y^W|X, \theta] + E[Y^H|X, \theta] E[D_M|X, \theta] \\
&= E[Y|X, \theta] + E[Y^H|X, \theta] \left\{ \sum_{j=1}^{J} E[D_j|X, \theta] E[D_M|X, \theta, s = j] \right\}
\end{aligned}
$$

The overall partial effect of psychological trait θ_k on family earnings is

$$\frac{\partial E\left[Y^F|X,\theta\right]}{\partial\theta_k} = \frac{\partial E\left[Y|X,\theta\right]}{\partial\theta_k} + \frac{\partial E\left[Y^H|X,\theta\right]}{\partial\theta_k}\left\{\sum_{j=1}^{J} E\left[D_j|X,\theta\right]E\left[D_M|X,\theta,s=j\right]\right\}$$

$$+ E\left[Y^H|X,\theta\right]\left\{\sum_{j=1}^{J}\frac{\partial E\left[D_j|X,\theta\right]}{\partial\theta_k}E\left[D_M|X,\theta,s=j\right]\right.$$

$$\left. + \sum_{j=1}^{J} E\left[D_j|X,\theta\right]\frac{\partial E\left[D_M|X,\theta,s=j\right]}{\partial\theta_k}\right\} \quad (4)$$

The derivatives of earnings expectations (such as term $\frac{\partial E[Y|X,\theta]}{\partial\theta_k}$) are equal to Eq. (3), for women's own earnings and husband's earnings. Note that husband's earnings, as a function of observables, are always based on the conditional wage distributions of husbands given that they are married to women in the sample. We are not interested in interpolating out these effects to the non-married men's population. The additional terms in Eq. (4) stem from the role of θ in determining not only husband's earnings when married but also the probability of being married $E\left[D_j|X,\theta\right]$. The direct effect of θ_k, holding constant schooling s, is simpler:

$$\frac{\partial E\left[Y^F|X,\theta,s\right]}{\partial\theta_k} = \frac{\partial E\left[Y|X,\theta,s\right]}{\partial\theta_k} \quad (5)$$

$$+\frac{\partial E\left[Y^H|X,\theta,s\right]}{\partial\theta_k}E\left[D_M|X,\theta,s\right] + E\left[Y^H|X,\theta\right]\frac{\partial E\left[D_M|X,\theta,s\right]}{\partial\theta_k}$$

$$= \underbrace{\delta_{j,k}}_{own} + \underbrace{\widetilde{\delta}_{j,k}E\left[D_M|X,\theta,s\right]}_{husb.earn.} + \underbrace{\frac{\partial E\left[D_M|X,\theta,s\right]}{\partial\theta_k}\left\{\theta\widetilde{\delta}_s + \widetilde{\kappa}_s + X\widetilde{\beta}\right\}}_{prob.married} \quad (6)$$

Conscientiousness, in fact, has a negative effect on the probability of marrying for women with a Master's degree or more.[18] At the same time, personality traits do not affect Y^H at all at this education level. Therefore, the overall effect on husband's earnings is negative, completely offsetting the positive effect on own earnings Y^W. More conscientious women are more likely to be in a high-wage job for an extended time. Thus, these women might have had more trouble finding a husband who would agree to such non-traditional behavior in his wife. Yet the causality is unclear: if a woman was unable to find a spouse to begin with, she had more incentives to obtain a full-time professional job to support herself. At this point, it is impossible to distinguish between these two hypotheses. At the Bachelor level or less, Conscientiousness has a double role in offsetting directions: more conscientious women at the Bachelor level marry higher earning husbands, but they are much less likely to marry.

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[18]Results from separate estimations not shown.

The overall effect is not distinguishable from zero.

In the effects of IQ, Openness, and Extraversion, the strong differential effects by education come to play. More extraverted women with at most a college education benefit greatly in terms of family earnings, coming from two positive effects: more extravert women are more likely to marry than introverts, and if they do they marry husbands with higher earnings. Women with a Master's degree or more, however, have statistically insignificant effects of extraversion on their husbands' earnings.

IQ is strongly *negatively* related to lifetime family earnings for women with a Master's or doctorate degree, but not for women with a bachelor's or less. Women of this highly select sample who obtained high education have lower earnings through husbands when their IQs are in the highest ranges as opposed to "just above 140." The large and surprising negative effect is actually not associated to the women's labor supply. Being of the highest IQ in this high-IQ group reduces a woman's probability of being married *if she also has a post-graduate education*, and thereby reduces husband's earnings, without increasing the probability of work.

Women with a bachelor's education who score higher on Openness will have lower spousal earnings, but their highly educated counterparts will have significant gains from this trait. This result stands in contrast to men, where Openness does not have significant direct effects on lifetime earnings.

4.3   The Direct Effects by Age for Men

When Eq. (1) is estimated age-by-age with education-varying coefficients $\delta_{j,t}$, the estimates are noisy and not significantly different from zero, or different from each other.[19] Whereas the null hypothesis $\delta_j = \delta$ can be rejected for several coefficients in the regression on lifetime earnings Y^T, it can not be rejected for all individual $\delta_{j,t}$. The main reason for the wide confidence bands of the estimates is that the number of observations is not very high (even though it is high given the unique high-IQ sample). Therefore, a sparser model that does not estimate the $\delta_{j,t}$ by education level is a valid benchmark for men, showing the effect of traits averaged over education levels. In the common coefficient model, all $\delta_{j,t}$ are forced to $\delta_{j,t} = \delta_j$:

$$Y_{j,t} = X_t \beta_t + \theta \delta_t + D_{j,t} \nu_{t,j} + \rho_{t,j}, \qquad t = 1, \ldots, T; j = 1, \ldots, J, \qquad (7)$$

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[19] See Fig. C-6 in Web Appendix Section C, 37. Figure C-7 shows the difference between the coefficients and the associated 95% confidence bands of the difference.

Figure 2 shows the results of estimates according to this common coefficient model, where indeed the standard errors are tighter.

IQ, even in this selective group, is still associated with higher earnings. This means that the lifetime effect of IQ is at least partly caused by a direct effect on earnings. This contradicts the claim by Gladwell (2008) that for the Terman men, IQ does *not* matter once family background and other observable personal characteristics are taken into account. **Conscientiousness** is strongly positively associated with earnings. For both IQ and Conscientiousness, the effects are always positive, but they are largest during the prime working years - from 40 to 60. One explanation for the strong effects which are absent from the early years could be related to work effort: Since the measure of earnings provided by the Terman data are only annual earnings, not hourly wages, it could very well be that more conscientious individuals work longer, and more hours. This would link back to the literature on the role Conscientiousness plays in health (Lodi-Smith et al., 2010). More conscientious individuals live longer (Friedman et al., 1993; Savelyev, 2012; Weiss and Costa, 2005). They are less likely to experience the chronic illnesses that are main predictors of mortality (Goodwin and Friedman, 2006; Marks and Lutgendorf, 1999; Mokdad et al., 2004), at least partly because they display better health-related behaviors, such as better prevention and fewer activities that endanger health (Roberts et al., 2005). Men who score highly on **Extraversion** have significantly higher earnings. Comparing two otherwise equal men where one scores one standard deviation higher on Extraversion, he will earn up to 20,000 USD (2010) per year more than his less outgoing counterpart. **Agreeableness** in the common coefficient model is not different from zero. **Neuroticism** also no longer affects earnings in the Terman sample significantly when the $\delta_{j,t}$ coefficients are restricted to δ_t.

The effects of Conscientiousness, Extraversion, and IQ only materialize when workers are in their thirties and after. At younger ages, the effects of personality traits are small and insignificant. Hause (1972) also found with the NBER-Thorndike data that ability played an increasing role with increasing age, as do Farber and Gibbons (1996) and Altonji and Pierret (1996).[20] Non-cognitive skills are also found to have effects on earnings that increase with age in Kuhn and Weinberger (2002), as leadership skills' effects only begin to emerge "some 7 to 8 years after high school."

There are two mechanisms that would explain this pattern. The first is employer learning. By this interpretation, increasing returns to skills reflect the sequential revelation of a worker's true ability, or the updating of the employer's beliefs (Altonji and Pierret, 1996,

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[20]Here, cognitive ability is approximated with performance on ability tests that are not purely the result of cognitive ability only: Hause (1972) measures ability with an Air Force test, Farber and Gibbons (1996) and Altonji and Pierret (1996) use the NLSY 79. For a discussion of the non-cognitive component of the ASVAB score, see Almlund et al. (2011) and the papers they cite.
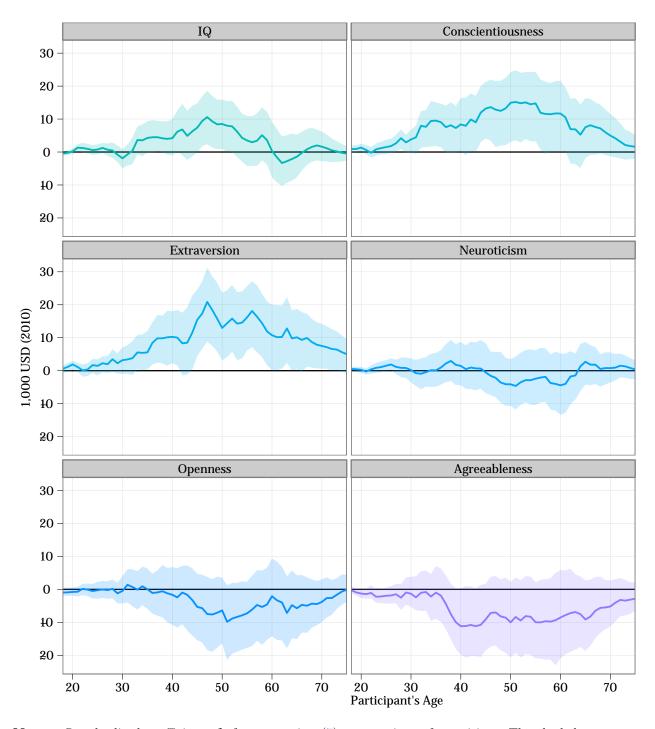
Figure 2: The Direct Effect of Personality and IQ on Earnings, Men, Common Coefficient

Notes: Standardized coefficients δ_t from equation (7), on earnings after tuition. The shaded areas are standard 95%-confidence bands from a bootstrap with 300 draws.

2001; Farber and Gibbons, 1996; Miller, 1984; ?). This is implied by Hause (1972), when he speaks of "learning capacity, information-handling ability" as playing a "larger role in earnings differentials over time as employers see improvement in the performance of people as they gain experience." These are opposed to specific skills necessary for jobs in the beginning which can be identified from school transcripts (compare to Spence, 1973). Initially, as employers do not yet observe a person's character traits or social skills, they cannot price these skills into wages. But while this explanation of rising returns to skills over time is a sound economic argument, the empirical evidence for this hypothesis in the context of personality traits is rather weak. The coefficients on interactions of skills with actual *tenure* are insignificant in Heineck and Anger (2010) and Nyhus and Pons (2005).

The second hypothesis that could explain the evolution of effects of social skills on wages with increasing experience is related to occupational sorting and hierarchies. Possibly, social skills start to matter meaningfully only once the workers has climbed the lowest rungs of the ladder and is in a leadership position himself. While being extraverted and conscientious is appreciated by his superiors at all levels, even while he is just an unimportant team member, these traits have a reasonably larger impact on other team members and, therefore, overall productivity, once he supervises others himself. This explanation is more directly related to the nature of these non-cognitive skills.

Having access to data that combines measures of personality traits and IQ with long follow-up is essential to pick up on this shape of effects by age. One can only describe the effects of these traits in a satisfying manner with earnings measures that extend well into the prime working years. Researchers who only have access to earnings observations for the early working life would likely find that these personality traits have no significant association, or very small ones, with earnings.[21]

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[21]A caveat about causality is in order. In contrast to the estimated effect of education on earnings, which can be interpreted as causal under the assumptions of this paper, the estimated effect of personality should be interpreted with caution. Researchers have debated whether reverse causality is a serious threat to validity in the analysis of the effect of personality on earnings. They are concerned with the possibility that personality traits in mid-life are affected by past earnings and labor market experiences. Then, an association of a certain trait with earnings is not necessarily causal. Most researchers use early measures of personality, so that these pre-date the outcome measures. This timing of measurements makes the interpretation of traits causing outcomes more credible. Yet, early traits are not hypothesized to cause outcomes, but concurrent traits. Thus, this method comes at the cost of not using the measure of personality that drives observed earnings (see Almlund et al., 2011).
This paper follows the approach of using early measures of IQ, Openness and Extraversion. However, the other personality traits are measured in 1940 — when the Terman participants are 25-35 years old. While claims of causality have to be guarded, the results can be interpreted as showing earnings gains due to personality and IQ. A robustness analysis was performed to test whether the 1940 measures of personality traits are a function of early labor market success. The personality factors are extracted conditionally on wages prior to 1940, wages at age 25, education, and age, and estimated the effects of these factors on wages (in the Web Appendix C, Section C.7). The estimated effect is not altered much by this conditioning.

For **women,** the estimates of direct effects of personality traits and IQ on earnings are generally more noisy than for men. The effect estimates are never statistically significant in the age-by-age version. The full set of figures for own and husband's earnings separately can be found in Web Appendix Section C.1.

5   Educational Attainment as a Function of Psychological Traits

Academic achievement and educational attainment have long been linked to IQ, motivation, and personality traits. An emerging economic literature has also shown psychological traits to be linked to educational attainment (Heckman et al., 2006). A summary is provided by Almlund et al. (2011), who report on findings from representative datasets in the U.S., The Netherlands, and Germany. Conscientiousness is consistently found to have a strong association with years of education, and its effect is the strongest among the psychological traits and exceeds that of IQ. More conscientious individuals stay in school longer. Extraversion, Agreeableness, and Neuroticism have weaker associations with education. Openness exhibits a positive association, but is known to be moderately correlated with IQ. Hence this finding could reflect the role of IQ rather than an own independent relation to schooling if IQ is not controlled for.

Based on a generalized ordered logit model of education choice, presented in Table 3, I find that psychological traits play roles that are similar to those found in the literature, but that the effects differ substantially by level of education, and by gender.

Conscientiousness is generally associated with higher schooling attainment for both men and women in this sample, even controlling for all background factors and other psychological traits. It is often found to be the strongest predictor of academic achievement, as in the survey by Noftle and Robins (2007). Conscientiousness likely enhances education through lowering the psychic costs of education, lowering the discount rate, and helping to imagine the future better. The "hard working" element of Conscientiousness implies that a conscientious person perceives the effort needed to achieve a higher educational attainment as less costly. The "future planning" element of Conscientiousness can be associated with lower discount rates for deferred gains. A greater propensity 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.

Openness is also significantly associated with higher education levels in the Terman sample, even conditioning on IQ. The effects of other psychological traits differ by gender.

Table 3: The Role of Psychological Traits on Education, Generalized Ordered Logit

	Some College		Bachelor's		Master's		Doctorate	
	Coef.	Std.Err.	Coef.	Std.Err.	Coef.	Std.Err.	Coef.	Std.Err.
				Males				
IQ	0.64	(.53)	0.36**	(.15)	0.11	(.10)	0.11	(.13)
Openness	−0.26	(.33)	0.41***	(.16)	0.13	(.14)	0.19	(.16)
Conscientiousness	0.31	(.27)	0.50***	(.16)	0.54***	(.14)	0.56***	(.16)
Extraversion	0.75	(.49)	−0.16	(.21)	0.00	(.14)	0.14	(.19)
Agreeableness	0.46	(.47)	−0.17	(.18)	0.03	(.15)	0.09*	(.19)
Neuroticism	−0.30	(.46)	0.51**	(.22)	0.29	(.18)	−0.13	(.20)
				Females				
IQ	0.31	(.35)	0.21	(.20)	−0.05	(.16)	−0.61**	(.60)
Openness	−0.26	(.56)	−0.06	(.21)	0.47*	(.21)	1.57***	(.62)
Conscientiousness	0.45	(.62)	0.35	(.23)	0.43***	(.19)	0.08	(.61)
Extraversion	−1.12	(.69)	−0.27*	(.21)	−0.03	(.19)	−1.30**	(.85)
Agreeableness	−1.86**	(.94)	−0.08	(.25)	0.01	(.23)	0.13	(.77)
Neuroticism	−2.72**	(.87)	−0.04	(.27)	0.00	(.24)	−0.36	(.60)

Notes:

The estimates in each column are the coefficients associated with the likelihood of passing each threshold. The generalized ordered logit model estimates the probability of passing a certain threshold, which in this case are "Some College" to "Doctorate." The estimates condition on the standard set of background controls in Table 1. Asterisks denote statistical significance based on a two-sided asymptotic test; * $p < .1$, ** $p < .05$, *** $p < .01$.

IQ significantly increases the chances of obtaining a Bachelor's degree or more for Terman men. Somewhat counterintuitively, women with a higher IQ are *less* likely to pass the threshold of a doctorate degree than Terman women with a lower IQ. This is less puzzling when one remembers that all Terman women had an exceptionally high IQ, so we are not comparing low-IQ women to high-IQ women, and that the threshold in question is very high. Only few women of this cohort obtained a doctorate degree (6%, vs 27% of males). This low percentage is in line with the evidence that this was an unusual and difficult path in the first half of the Twentieth century. In fact, even in a younger cohort (born around 1944), the share of mathematically gifted women with doctorate degrees was much lower than for men (5% versus 30%, in Lubinski and Humphreys 1990).

The associations between education and Extraversion, Agreeableness, and Neuroticism for Terman females are similar to findings in previous studies, where representative samples of men and women were used. Compared to estimates from these samples where men and women were pooled together, the associations for Terman males diverge here when they are estimated separately. The effect of **Extraversion** on educational choice is negative for females. For Terman men, extraversion has no significant effect on educational attainment, which is not what other researchers find. One expects a negative effect (socializing takes time away from studies), and it has indeed been found in previous studies for representative samples of men and women (such as O'Connell and Sheikh, 2011). **Agreeableness** and **Neuroticism** negatively affect the choice of education above high school for females, which is in line with previous results on the effects of Agreeableness and Neuroticism on the educational choices of men and women in the general population. Neuroticism *increases* the likelihood of choosing at least a bachelor's degree for men.

6   The Rate of Return to Schooling

Having established that psychological traits determine educational choice, we can ask how education translates into lifetime earnings. One common way of summarizing this information is through the internal rate of return (IRR).[22] Standard procedures developed by Becker and Chiswick (1966) and Mincer (1974) make strong assumptions to use cross sectional data to estimate life-cycle rates of return.[23] Because the Terman data provides complete life-cycle earnings data, these assumptions are not necessary here. Also, instead of relying on years of schooling as the regressor, I contrast different levels of education in pairwise comparisons.

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[22]This is the discount rate that would make an individual indifferent between two options: obtaining more education or remaining at a baseline level (j vs. k). It is the ρ that solves the polynomial $\sum_{t=18}^{75} \frac{(\kappa_{j,t} - \kappa_{k,t})}{(1+\rho)^t} = 0$. From Eq. (1), we have the causal effects of education $\kappa_{j,t}$ at all ages $t = 18, ..., 75$.

[23]Heckman et al. (2006) review the literature which is based on this approach.

This yields a richer picture of the different trade-offs that individuals face when choosing one education level over another. The Mincer specification performs poorly in comparison.

Furthermore, a drastic departure from the traditional rate-of-return analysis results from the interactions established in Section 4. The rate of return to education is significantly higher for men who are highly extroverted, conscientious, and emotionally stable.

6.1 The Mincer Coefficient

Most rates of return in the literature are not actually estimates of the internal rate of return. It is common practice to estimate a Mincer equation and interpret the coefficient on years of schooling as the rate of return. Even though the Terman data are longitudinal, one can estimate the Mincer equation as if the data were cross-sectional. Regressing log wages on years of schooling, experience and its square, the Terman Mincer rate of return for males is 7.5%. For women, it is 6.0%, and for their combined earnings with their husbands it is only 3.6%.[24]

The standard Mincer regression does not include other covariates, but if personality traits are included as regressors, the Mincer coefficient for men drops to 6.5%, and it drops further to 6.3% when IQ is controlled for. This decrease is commonly associated with "ability bias" (Griliches, 1977) - even though most researchers have only cognitive ability or IQ in mind and not other aspects of ability. In comparison to Blackburn and Neumark (1995), the decrease in Terman data from including IQ is much smaller than their 40%. In this sample with a restricted IQ range, omitting non-cognitive abilities or personality traits is of greater importance.

In comparison to the numbers one typically expects for Mincer coefficients, the 7.5% for men is at the OECD average during the 1990s (Psacharopoulos and Patrinos, 2004), but lower than typical US figures (Card, 1999). Of course, these well-known Mincer estimates are for more recent cohorts and a comparison with estimates from the 1950 census[25] is more appropriate. The Mincer coefficient for synthetic cohorts from the 1950 census is 9%, which is still higher than the Terman estimate. In fact, if the Terman earnings were top-coded as in the census, the Mincer rate of return would only be 3.9%. These comparisons might lead us to conclude that returns to education at the very high end of IQ are low, that "geniuses"

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[24]For this comparison, all observations in the treatment-estimation sample are used, ages 18-65, as if they were from a cross-section. Years of schooling are imputed from degrees and experience is approximated by subtracting six and the number of years of schooling from the participants current age, as is customary. Then, log wages are regressed on years of schooling, experience, and its square. In a second estimation, the regressors are enriched by the set of psychological traits and background variables as in our standard estimation.

[25]The IPUMS sample, described by Ruggles et al. (2010), was used.

do not need formal training. This conclusion would be faulty, however, as the Mincer return does not correspond to the true pairwise rates of return, and masks a large variation in returns that can be observed for the different education levels.

6.2 The IRR for Men

The average treatment effect of education level j vs. k at each age t corresponds to $\kappa_{j,t} - \kappa_{k,t}$ from Eq. (1). At the mean, factor scores are zero, therefore in these average effects, the impact of psychological traits drops out.[26]

The pairwise estimates of average treatment effects are plotted in Fig. 3. Schooling always has a negative effect on annual earnings in the early years of a working life since individuals who are obtaining more education are still in school while their peers with less education are already out of school and working. The following positive effect of education is substantial during the prime working years, a standard result in the literature (Becker, 1964).

The IRRs and Net Present Values (NPVs) corresponding to the estimated average effects are listed in each graph, and the complete list of IRRs and NPVs is listed in Table 4.[27]

The pairwise treatment effects are clearly different from each other and cannot be summarized in a single "rate of return" as one would obtain from the Mincer coefficient. In comparison to having a high school diploma, obtaining a bachelor's degree increases the Terman males' earnings by \$379,200 over a lifetime, if the difference in earnings is discounted at 3%. The corresponding IRR is 12.5%. This estimate implies 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 return on equity.[28]

How does this compare to an estimate from the census? If we estimate the differences between schooling levels nonparametrically as in Heckman et al. (2006), and treat the Terman data as census data (including top-coding), we obtain Fig. 4. With this methodology, the Terman rate of return to a bachelor's degree is lower than from matching (and not top-coded). It is smaller than the census return, despite the higher earnings of Terman men

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[26]This means that the second term, $\theta(\delta_{j,t} - \delta_{k,t})$, evaluates to zero at the mean, since the θ have mean zero. In the limit, the average treatment effect of education as estimated from Eq. (1) is equal to the estimates from Eq. (7), as the personality traits and IQ are normalized to have mean zero.

[27]In principle, an IRR should be compared to the market interest rate to determine the optimality of schooling. IRRs are not suited to compare three alternative investments to each other (Ross et al., 2001). For example, the IRR of "some college" over high school is very similar to that of a bachelor's over high school— but this is a result only of the small up front costs, combined with small absolute gains later on. The NPV is better suited to compare several alternatives, and it shows that the bachelor's is an investment that is more attractive (net gains of \$379,200 rather than \$116,400).

[28]The S&P 500 annualized return from 1928 to 1985 (when the Terman men were on average 18–75 years old), is about 6%.
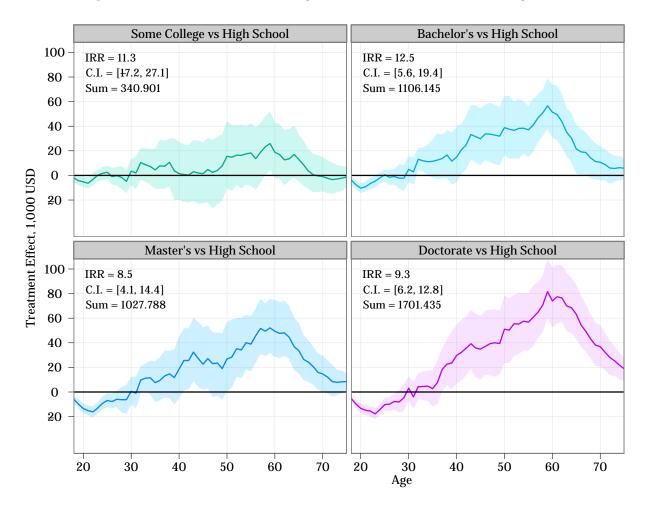
Figure 3: Select Pairwise Average Treatment Effects on Earnings, Males

Notes: Age-by-age treatment effects from Eq. (1), evaluated for males with average personality traits, and 95% confidence bands from 300 bootstrap draws. The corresponding Internal Rate of Return (IRR) and its Confidence Interval (C.I.) are listed in the graphs, with the total undiscounted lifetime effect of education is given in "Sum." Table 4 lists the net present value discounted at 3%. Earnings are annual earnings after tuition in 2010 U.S. Dollars, with the top 3% values truncated. Covariates are IQ, factor scores for personality traits, parental background, family environment, childhood health, and controls for WWII and cohort. The full set of treatment effect curves are available in Web Appendix Section C.1.

Table 4: Pairwise Average Treatment Effects on Earnings, Males

	Internal Rate of Return				Net Present Value, discounted at 3%			
	Some Coll.	Bachelor	Master	Doctorate	Some Coll.	Bachelor	Master	Doctorate
High School	11.3 [-17.2, 27.1]	12.5 [5.6, 19.4]	8.5 [4.1, 14.4]	9.3 [6.2, 12.8]	116.4 [-153, 425]	379.2 [123, 663]	302.2 [43, 624]	497.6 [244, 790]
Some College		13.4 [2.2, 21.7]	7.5 [2.1, 13.5]	8.9 [5.5, 12.5]		264.8 [36, 470]	187.8 [-50, 427]	383.2 [162, 627]
Bachelor			-2.3 [-13.8, 63.8]	5.9 [1.8, 11.5]			-75.0 [-284, 125]	120.5 [-74, 327]
Master				13.0 [-5.1, 23.9]				197.4 [6, 415]

Notes: Internal Rate of Return (IRR) and its Confidence Interval (C.I.), and net present value discounted at 3% with confidence intervals, corresponding to the age-by-age effects shown in Fig. 3. Earnings are annual earnings after tuition in 2010 U.S. Dollars, with the top 3% values truncated. Covariates are IQ, factor scores for personality traits, parental background, family environment, childhood health, and controls for WWII and cohort. The full set of treatment effect curves are available in Web Appendix Section C.1.
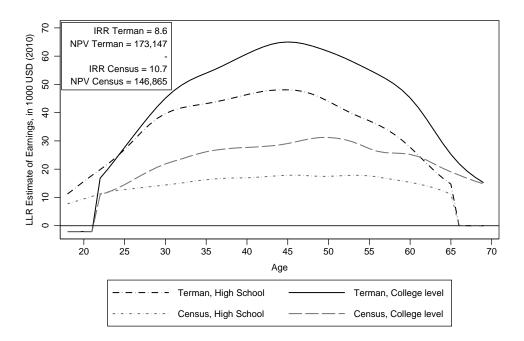
28

Figure 4: IRR and Mean Earnings by Education in Terman and Census, Males

Notes: Local linear regression estimates of earnings in Terman and 1950 census, as in Heckman et al. (2006), comparing census men with 12 and 16 years of schooling to Terman men with a high school diploma only (no college) and a bachelor's degree. Terman earnings are treated as census data, and are topcoded at the 1950 values. All earnings are set to zero during college. Net present values are discounted at 3%.

versus the census average. The reason why the return is lower is that at both education levels, Terman earnings are higher - therefore, education makes a smaller relative difference. Since Terman men with a high school diploma earn substantially more than the average man from the census, the opportunity cost of schooling is much higher.

Obtaining a master's degree in comparison to a bachelor's has a negative IRR at -2.3%. For the person with average levels of all psychological traits, obtaining a doctoral degree over a bachelor's increases lifetime earnings, but only by a net present value of $120,500).

Looking at IRRs only could lead us to the conclusion that post-graduate degrees are worse investments than a simple college degree, but the NPVs reflect the large absolute gains that outweigh the long up front investments. At IRRs of 8.5% and 9.3%, the doctoral degree leads to even higher discounted earnings gains than the master's degree ($497,600 vs $302,200).

Even in a high ability group, education adds skills that are valued on the marketplace. The returns to schooling are real, and ability bias cannot be responsible for the type of returns we find.

6.3 The IRR for Women, Family Earnings Decomposed

The women in the Terman sample belonged to a generation in which the role of the woman was still mainly that of a homemaker, mother, and wife (see Goldin, 1992). Society defined very strictly what type of occupations were deemed "suitable" for a woman, and a woman's freedom to choose her career or define her own lifestyle was not what it is today. Thus, we should expect a high share of housewives among the Terman women. About half of the Terman women did not engage in paid work, despite their extraordinary abilities and talents.
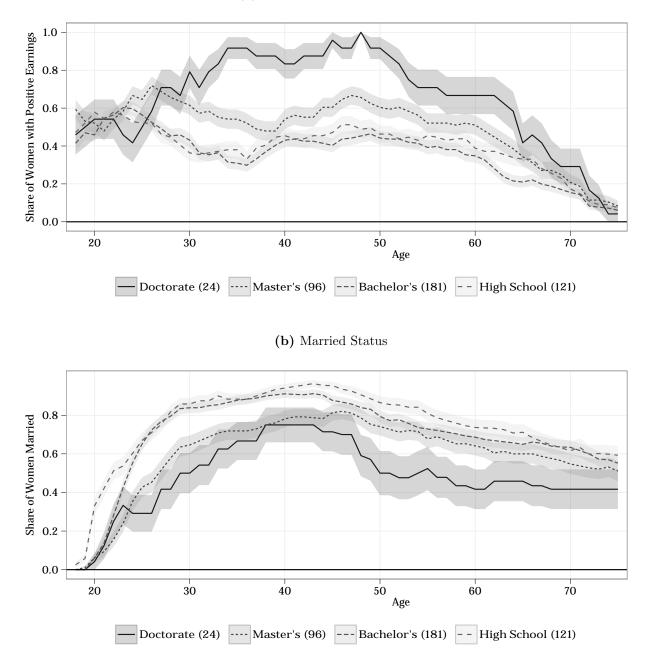
Many women of this cohort were mainly housewives and did not earn a market wage, but they could still benefit from education by finding a better match, a husband with higher educational achievement and earnings, and thus increase their potential family earnings. A Terman woman with postgraduate education was more likely to be in gainful employment and less likely to be married than her peers with at most a Bachelor's degree, as Fig. 5 shows. Whether this relationship between education and labor supply or marital status is causal is far from clear. For example, a highly educated woman might have chosen to focus her energy on a career early on, and with own earnings would have been less dependent on finding a husband. Also, her high education and career aspirations may have made her less attractive as a marriage partner. It is also possible that causality moves in the other direction. For example, she might not have found a husband initially, and thus decided to obtain more schooling in order to support herself.

Figure 7 decomposes the effect of education on women's family earnings into its effect on their own earnings and on their husband's earnings (which is the effect through marriage). Women with post-graduate education greatly improved their **own earnings**. The treatment effect of a master's degree is positive but remains small and is not statistically significant. For women with a doctorate degree, the returns to education are substantial, and even higher in terms of IRRs than men's.

The combined effect of education on **family earnings** is shown in the solid black line, and the corresponding IRRs are shown in the box. The treatment effect on family earnings is dominated by the very large effect on their own earnings for women with a doctoral degree — it completely washes out the slightly negative effect that education has on husband's earnings. But these women were very special cases. They worked in high-ranking jobs, had high earnings, and did not rely on their husbands to provide their earnings.

The returns to education in terms of family earnings are also positive for women with a bachelor's degree, because they benefit from the marriage market. Again, the **gains from education through marriage** through husband's earnings can be decomposed into the effect of education on the probability of being married, and on conditional husband's

Figure 5: Women's Labor Market Participation and Marriage Histories

(a) Labor Market Participation

(b) Married Status

Notes: Observation counts are given in parentheses. The indicator for employment is given by positive own earnings. The indicator for being married is given at each age, and excludes those who are currently married but separated. The education categories refer to the highest educational level the subjects attained in life. See the Web Appendix for other graphs, as well as information on building the earnings profiles, and the marriage history, from the raw data.
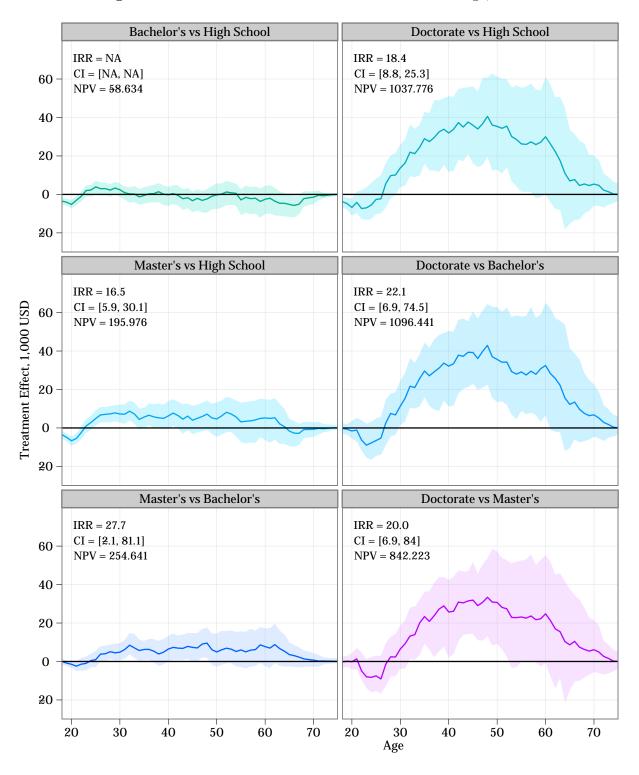
Figure 6: Pairwise Treatment Effects on Own Earnings, Females

Notes: Average treatment effects of education on own earnings, from the estimation Eq. (1). Corresponding to these lifetime effects are the internal rate of return (IRR) with bootstrapped 95% confidence bands, and net present value (NPV) at a 3% discount rate.

earnings. The direct effect of education level j versus education level k on husband's earnings is

$$E\left[Y^M|s=j,X,\theta\right] - E\left[Y^M|s=k,X,\theta\right] = \tag{8}$$
$$\left\{\theta\widetilde{\delta}_j + \widetilde{\kappa}_j + X\widetilde{\beta}\right\} E\left[D_M|X,\theta,s=j\right] - \left\{\theta\widetilde{\delta}_k + \widetilde{\kappa}_k + X\widetilde{\beta}\right\} E\left[D_M|X,\theta,s=k\right]$$

The gains from education are positive for women with a bachelor's degree over high school. Yet for education levels beyond the bachelor's, higher education is associated with slightly *lower* earnings through marriage. The more highly educated women are less likely to be married, and thus lose the opportunity to bolster their own earnings with their husband's. Thus, the rate of return is negative because the return through own earnings is not enough to offset the losses in the marriage market.[29]

Figure 8 explores these different effects: It shows two counterfactual treatment effects of education on the women's gains through marriage. The first counterfactual describes the case when the propensity to be married did not differ by education. Say, it is one for all education groups. Then

$$E\left[Y^M|s=j,X,\theta\right] - E\left[Y^M|s=k,X,\theta\right] = \theta\left(\widetilde{\delta}_j - \theta\widetilde{\delta}_k\right) + \left(\widetilde{\kappa}_j + \widetilde{\kappa}_k\right)$$

The solid line represents this case where education only affects the quality of matches. For women with a bachelor's or doctorate degree, education improves match quality. Women with a master's were not able to find higher-earning husbands than less-educated women, leading to a negative return through match quality.

The second counterfactual describes the environment where the propensity to be married is influenced by education, but not the match quality. In that case, husbands' earnings were the same regardless of the woman's education, say $\theta\widetilde{\delta} + X\widetilde{\beta}$, and

$$E\left[Y^M|s=j,X,\theta\right] - E\left[Y^M|s=k,X,\theta\right]$$
$$= \left(\theta\widetilde{\delta} + X\widetilde{\beta}\right)\left\{E\left[D_M|X,\theta,s=j\right] - E\left[D_M|X,\theta,s=k\right]\right\}$$

The dashed line corresponding to this second counterfactual shows that marriage prospects clearly declined increasingly with education past a bachelor's degree. The lower marriage propensity outweighs the effect of education on match quality, leading to negative returns to education through husbands.

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[29]The rate of return of a master's degree over the high school diploma cannot be computed because there are multiple crossings with the zero line, and there might simply not exist a rate of return that would set the net present value of this investment to zero.
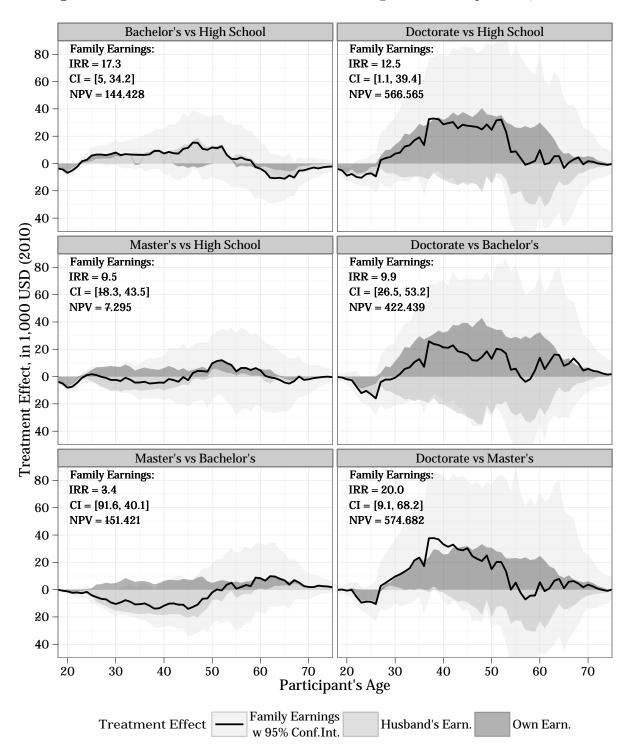
Figure 7: Pairwise Treatment Effects on Earnings and Decomposition, Females

Notes: Average treatment effects from estimation Eq. (1), on three measures of annual earnings in 2010 U.S. Dollars: Terman female's earnings, their husband's earnings, and the combined family earnings (solid black line, light grey area is the 95% confidence band from 300 bootstrap draws). Corresponding to these lifetime effects are the internal rate of return (IRR) with bootstrapped 95% confidence bands, and net present value (NPV) at a 3% discount rate.
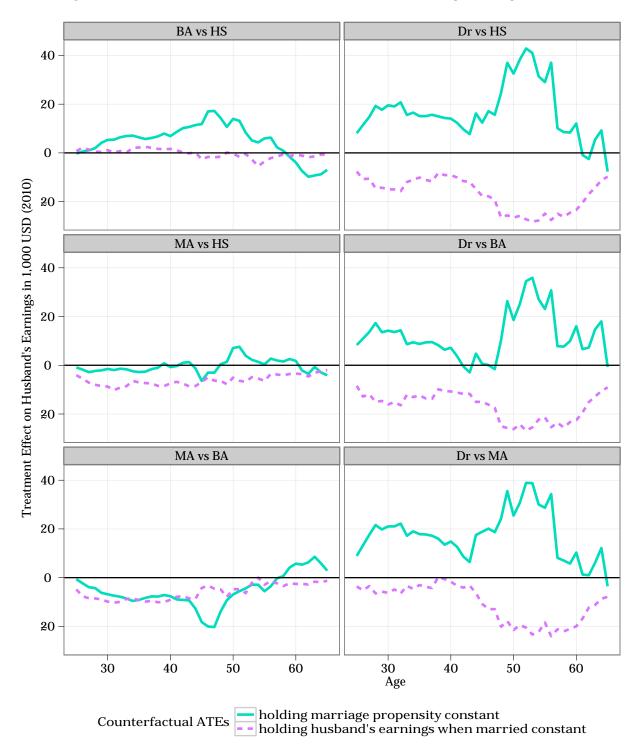
Figure 8: Counterfactual Effects of Education on Earnings through Husbands

Notes: Counterfactual average treatment effects from estimation Eq. (1) on husband's earnings. "Holding marriage propensity constant" shows how education affects the husband's earnings, assuming all women are married. "Holding husband's earnings when married constant" assumes all husbands earn the same, and education affects only the probability of being married.

Most interestingly, the exceptional women who obtained a Doctorate degree did not suffer significantly in the marriage market, as one might have anticipated. Even though they were significantly less likely to be married, conditional on being married, their husbands had higher-than-average earnings, so the overall impact of their high education on the returns to marriage are not statistically different from zero.

In the lifetimes of the Terman cohort, women's opportunities to increase their earnings through education were more limited for women than they were for men. Women's own earnings mostly fell short of the earnings of men with the same level of education and ability; not only due to the choice of occupation, but also within occupation. At the same time, marriage prospects were not always boosted by higher education, and only increased earnings sufficiently for women with a college education to offset their smaller market returns. For them, the rates of return to education were similar to those of Terman men.

7   Conclusion

This paper estimates the effects of personality traits and IQ on lifetime earnings of the high-achieving men and women of the Terman study. Personality traits and IQ affect the levels of earnings, especially in the prime working years. They also affect educational sorting and thus command an indirect effect on lifetime earnings. Furthermore, there is a significant interaction between education and traits in producing earnings. Therefore, the treatment effect of schooling is a function of personality traits. By the unique access to the full lifetime earnings histories, these heterogeneous effects can be disentangled, whereas in an age-by-age estimation, they fail to be statistically significant.

Psychological traits are priced directly in the marketplace for men, but not for women of this cohort. Men gain from traits such as Conscientiousness, Extraversion, and IQ. Women with up to a Bachelor's degree are able to gain from Extraversion by matching to higher-earning partners.

The presented estimates of the internal rate of return to education do not rely on the strong assumptions that are standard in the literature to estimate the "rates of return." Instead, the returns are based on causal effects, obtained by matching on an unusually extensive list of covariates, including IQ and personality. The analysis of the returns to education for persons at the high end of the IQ distribution is unique.

The returns for the Terman men are sizeable. For women at education levels below the doctoral level, the rates of return are low. But there are gains through sorting in the marriage market for women with a college education. Women with a doctorate degree have very high earnings on their own, and their rates of return are even higher than those of men.

The findings presented here contribute to the literature on childhood interventions that focus on social skills. Social skills or personality traits have profound influences on life outcomes and they are more malleable past early childhood than, for example, IQ. Therefore, they point to a promising avenue of reducing inequality and providing development opportunities, which actually circumvent the traditional efficiency-equity tradeoff due to their positive rates of return. The literature has not yet analyzed whether personality traits play a similarly important role for children at the other end of the spectrum (i.e., high-ability children). This paper shows that indeed, men earn substantially more if they possess strong social skills. The increase in discounted lifetime earnings corresponds to about half of the effect of obtaining a bachelor's degree over high school only. Highly-able individuals are therefore also likely to benefit from interventions targeted at improving their social skills.

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