Talented individuals are seen as drivers of long-term growth, but what makes them realize their full potential? In this paper, I show that lifetime earnings of high-IQ men and women are substantially influenced by their personality traits, in addition to intelligence. Personality traits directly affect men’s earnings, where the effects only develop fully after age 30 and increase in education. Personality and IQ also influence earnings indirectly through education, which has sizeable positive rates of return for men in this sample. For women, born early in the 20th century, returns to education past a bachelor’s degree are reduced through worse marriage prospects, which offset gains to education in terms of own earnings. The causal effect of education is identified through matching on detailed background information. This paper complements the well-established results regarding the role of education and personality traits in explaining life outcomes of disadvantaged children by demonstrating that they also account for considerable variation in lifetime productivity at the opposite end of the ability distribution.

Key words: lifetime earnings, cognitive skills, social skills, factor analysis, human capital, returns to education

JEL codes: J24, J16
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1 Introduction

This paper draws on a unique sample of high-ability men and women born early in the last century and followed over their lifetimes by the American psychologist Lewis Terman.\footnote{The study is described in Terman and Sears (2002a); Terman et al. (2002a) and Terman and Sears (2002b); Terman et al. (2002b). It is the longest prospective cohort studies in existence, Friedman et al. (1995).} The Terman study contains rich data on the lifetime earnings, psychological traits and family backgrounds of a cohort of high IQ men and women. These unique individuals were all expected to excel in life, to be over-achievers and contribute to society by the sheer power of their talent. While many of them fulfilled this expectation, their life outcomes varied greatly. I show that a substantial amount of this variation in lifetime earnings can be explained by personality traits, in addition to intelligence, and education. Psychological traits have significant direct effects on earnings. These direct pricing effects do not arise until age 30 or later. Furthermore, their magnitude is increasing in schooling — the effects are stronger for the more highly educated men. In individual year-by-year estimates, these differences are not statistically significant. Therefore, standard data sets, which do not contain life time earnings data, would not identify this heterogeneity.

There are also indirect effects of personality traits and IQ on lifetime earnings, since they alter educational attainment, and there are significant positive returns to schooling in this sample.

I also analyze the effects of intelligence at very high levels. The data used in this paper do so. IQ has a positive and statistically significant effect on men’s earnings, even within the IQ range of 140–200. This effect does not only work through higher educational attainment but also from a direct impact of ability on earnings. For women, in contrast, having a higher IQ results in lower lifetime earnings if they were not at the top of the educational attainment spectrum.

The cohort studied here was born in the early years of the last century when the role of women in the labor market and society was fundamentally different than it is today (Goldin,
Counting only their own earnings, the rate of return to female schooling is low for women with less than a doctorate degree. Assortative mating leads to more profitable matches for the more highly educated women, so education should increase their family earnings. There is, however, an additional cost to post-graduate education for women of this cohort: their prospects of marrying are much lower, offsetting the positive effects of education on family earnings. Finally, women with a doctorate degree were exceptional figures who had earnings almost as high as men.

With access to lifetime earnings histories, I can bypass the *ad hoc* methods widely used to approximate the lifetime *ex post* rate of return from cross sections of data. Using full life cycles of earnings, I present estimates of the internal rate of return to schooling and show that it is a function of psychological traits as well. Standard application of the Mincer model produces misleading estimates.

The paper proceeds in the following way. Section 2 discusses the rich data analyzed in this paper. Section 3 discusses the effects of psychological traits on earnings levels and rates of return by gender, separated into the direct and indirect effects. Section 4 concludes.

## 2 The Terman Survey

The analysis in this paper is based on a survey initiated by the prominent psychologist Lewis Terman in the early 1920s to study the life outcomes of high IQ children. The criterion for inclusion in the sample was having an IQ of 140 or higher. These high IQ school children were identified through a procedure that canvassed all high schools in California. The Terman sample consists of 856 boys and 672 girls, born around 1910. The cohort was followed from 1922 to 1991, with surveys every 5–10 years, making it the longest prospective cohort.
study that also has data on earnings.\textsuperscript{6} Using these, we can estimate earnings parameters using life cycle data and not synthetic cohorts and avoid imposing the assumptions of the Mincer model which in other research has been tested and rejected (Heckman et al., 2006).\textsuperscript{7}

The Terman data is not only unusual in terms of its long follow up, but also, and possibly even more so, in terms of its 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. The Terman survey samples high-ability individuals who are rarely found in standard surveys. Given the low correlation between IQ and most personality traits,\textsuperscript{8} we can generalize our findings on the effect of personality on earnings and other outcomes to the wider population.

The sample used to conduct the analysis does not include the youngest and oldest participants, since their selection into the sample was non-standard.\textsuperscript{9} Our sample consists of 766 men and 607 women who were born between 1904 and 1915. We use respondents with valid information about their education who have observations available on all socio-emotional trait ratings. We exclude non-Caucasian children and those with rare genetic diseases. In order to have full earnings histories from age 18 to 75, only individuals with 10 or fewer

\textsuperscript{6} Its attrition rate is less than 10%. Those who dropped out from the sample do not differ from those who remain in terms of income, education, and demographic factors (Sears, 1984), or psychological measures (Friedman et al., 1993a).

\textsuperscript{7} The Terman data have been used extensively by psychologists but much less so by economists. Psychologists have focused on health and longevity outcomes. They have linked longevity to the personality trait of conscientiousness (Friedman, 2000, 2008; Friedman et al., 1994, 1995, 1993a; Martin et al., 2007, 2002), as well as to parental divorce, durations of marriage, and number of children (Friedman et al., 1995; Martin et al., 2005; Schwartz et al., 1995; Tucker et al., 1997, 1996, 1999). The economists analyzing this data analyze family outcomes: Becker et al. (1977) discusses marital instability, Michael (1976) divorce, and Tomes (1981) fertility and children's schooling. The Terman retirement behavior is analyzed by Hanermesh (1984). Savelyev (2011) investigates the causal effect of higher education on longevity and the role of Conscientiousness. Only the work by Leibowitz (1974) focuses on earnings outcomes. She estimates the effect of schooling on earnings, controlling for parental investments in their children, but the longitudinal feature of the data is ignored. Today, I have many more years of lifetime data than she does.

\textsuperscript{8} See Borghans et al., 2011 for a discussion of the correlation of IQ and personality traits. Note that Openness to experience is an exception to the low correlation, this trait is consistently found to be positively correlated to IQ.

\textsuperscript{9} As described in Terman et al. (1925), 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.
years of missing earnings information are retained in the sample. The sample consists of 595 men and 422 women.

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. 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. Note that for inactive workers, who are no longer working, as well as for the deceased, earnings are set to zero but still included in the profile.

The raw earnings profiles by education are presented in Fig. 1. They follow the standard pattern of initially higher earnings for persons who obtain less schooling, which are later surpassed by the earnings of the more educated, once they work full-time.

2.1 IQ and Personality Measures in the Terman Sample

IQ is measured at study entry in 1922, and is the basis for inclusion in the Terman sample. 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 the Big Five were codified.

Personality ratings are measured in 1922 and 1940. Table A-3 in the Web Appendix

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10 The Web Appendix A, found at http://home.uchicago.edu/~mgensowski/research/Terman/Terman-App.pdf, describes how the earnings profiles were constructed and specifies how tax rates or tuition costs are obtained.

11 The Web Appendix C provides all of the estimates made here in this paper also on earnings after tuition and tax, where tax rates are made a function of the marital status obtained from the Terman marital histories.

12 Most students took the Stanford-Binet IQ test. About 30% of the students took another IQ test, the closely related “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). In order to control for possible differences between the two measures of IQ, we allow for different regression coefficients on the different measures of IQ. They are not statistically different from each other so we do not report these results.

13 See Goldberg (1993). The Big Five traits are Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism (OCEAN). While our traits 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 Conscientiousness and Extraversion from the Terman questionnaires correspond closely to the analogous Big Five traits.
Figure 1: Average Earnings by Education, Minus Tuition and After Taxes

(a) Males

(b) Females (family earnings)

Notes: Observation counts are given in parentheses. Earnings are average annual earnings minus tuition, in thousand 2010 U.S. Dollars, constructed from Terman Data. For women, earnings are their own as well as their husband’s earnings (if they are married). 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 education categories refer to the highest educational level attained in life. See the Web Appendix http://home.uchicago.edu/~mgensowski/research/Terman/TermanApp.pdf for information on building the earnings profiles, tuition, and the marriage history, from the raw data.
<table>
<thead>
<tr>
<th>Control Variable</th>
<th>Year</th>
<th>Males Mean (Std.dev)</th>
<th>Females Mean (Std.dev)</th>
</tr>
</thead>
<tbody>
<tr>
<td>IQ</td>
<td>1922</td>
<td>149.4 (10.90)</td>
<td>148.6 (10.34)</td>
</tr>
<tr>
<td>Openness</td>
<td>1922</td>
<td>0.00 (0.85)</td>
<td>0.00 (0.73)</td>
</tr>
<tr>
<td>Conscientiousness</td>
<td>1940</td>
<td>0.00 (0.89)</td>
<td>0.00 (0.71)</td>
</tr>
<tr>
<td>Extraversion</td>
<td>1922</td>
<td>0.00 (0.70)</td>
<td>0.00 (0.82)</td>
</tr>
<tr>
<td>Agreeableness</td>
<td>1940</td>
<td>0.00 (0.66)</td>
<td>0.00 (0.57)</td>
</tr>
<tr>
<td>Neuroticism</td>
<td>1940</td>
<td>0.00 (0.59)</td>
<td>0.00 (0.55)</td>
</tr>
<tr>
<td>Father's highest school grade</td>
<td>1922</td>
<td>12.34 (3.61)</td>
<td>12.10 (3.62)</td>
</tr>
<tr>
<td>Mother's highest school grade</td>
<td>1922</td>
<td>11.57 (2.83)</td>
<td>11.69 (2.95)</td>
</tr>
<tr>
<td>Father's occupation: clerical or deceased</td>
<td>1922</td>
<td>26% (0.44)</td>
<td>24% (0.43)</td>
</tr>
<tr>
<td>Father's occupation: low-skilled</td>
<td>1922</td>
<td>16% (0.37)</td>
<td>15% (0.36)</td>
</tr>
<tr>
<td>At least one parent is retired or deceased</td>
<td>1922</td>
<td>3% (0.18)</td>
<td>4% (0.19)</td>
</tr>
<tr>
<td>Mother has occupation (not minor)</td>
<td>1922</td>
<td>11% (0.32)</td>
<td>10% (0.30)</td>
</tr>
<tr>
<td>Father's age when child was born</td>
<td>1922</td>
<td>33.42 (8.00)</td>
<td>34.17 (7.67)</td>
</tr>
<tr>
<td>Mother's age when child was born</td>
<td>1922</td>
<td>28.64 (5.39)</td>
<td>29.54 (5.36)</td>
</tr>
<tr>
<td>Either parent is born in Europe</td>
<td>1922</td>
<td>13% (0.34)</td>
<td>12% (0.32)</td>
</tr>
<tr>
<td>Childhood family finances (very) limited</td>
<td>1950</td>
<td>38% (0.49)</td>
<td>38% (0.49)</td>
</tr>
<tr>
<td>Childhood family finances abundant</td>
<td>1950</td>
<td>4% (0.20)</td>
<td>6% (0.23)</td>
</tr>
<tr>
<td>Childhood parental social status - high</td>
<td>1950</td>
<td>35% (0.48)</td>
<td>33% (0.47)</td>
</tr>
<tr>
<td>Number of siblings</td>
<td>1940</td>
<td>1.8 (1.60)</td>
<td>1.8 (1.62)</td>
</tr>
<tr>
<td>Birth order</td>
<td>1940</td>
<td>1.8 (1.27)</td>
<td>2.0 (1.39)</td>
</tr>
<tr>
<td>No breastfeeding</td>
<td>1922</td>
<td>9% (0.29)</td>
<td>9% (0.29)</td>
</tr>
<tr>
<td>Birthweight in kilograms</td>
<td>1922</td>
<td>3.8 (0.65)</td>
<td>3.6 (0.63)</td>
</tr>
<tr>
<td>Sleep is sound</td>
<td>1922</td>
<td>97% (0.17)</td>
<td>98% (0.14)</td>
</tr>
<tr>
<td>Cohort: 1904-1910</td>
<td></td>
<td>56% (0.50)</td>
<td>53% (0.50)</td>
</tr>
<tr>
<td>Cohort: 1911-1915</td>
<td></td>
<td>44% (0.50)</td>
<td>47% (0.50)</td>
</tr>
<tr>
<td>WWII combat experience</td>
<td>1945</td>
<td>10% (0.30)</td>
<td>0% (0.07)</td>
</tr>
</tbody>
</table>
presents the items used to measure each trait. Two personality traits are measured in 1922: Openness and Extraversion. Extraversion is indicated by the subject’s “fondness for large groups,” “leadership,” and “popularity with other children” as rated by teachers and parents (where we take the average of both ratings). Openness is extracted from ratings of the subject’s “desire to know,” “originality,” and “intelligence.”

The other three traits are based on self-ratings in 1940: Conscientiousness, Agreeableness, and Neuroticism. The dedicated items for each are either from the personality inventory, 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 “persistence” or “In your work do you usually drive yourself steadily?” Neuroticism is based on measurements on “moodiness” or “Are your feelings easily hurt?” etc. Agreeableness items are, for example, “easy to get along with,” or “Are you always careful to avoid saying anything that might hurt anyone’s feelings?”.

### 2.2 Education and Background Variables

We have detailed information on the educational status and attainment of the Terman participants. We also have information on 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).

Descriptive statistics of the covariates that will be used as control variables are listed in Table 1. Further descriptive statistics of variables used in this paper are presented in Appendix Tables A-1 and A-2.

---

14 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 (r = .16, significantly different from zero). Other personality traits have much lower correlations with IQ.

15 The Bernreuter scale (see Terman et al., 2002a).
3 The Effects of Psychological Traits on Earnings and the Rate of Return to Schooling

IQ and personality traits, at least some of them, influence lifetime earnings of men and women in the Terman sample. The association between the sum of discounted lifetime earnings and these traits is discussed in Section 3.1. But observing that psychological traits are associated with total earnings does not tell us where, or when these traits might influence earnings. One can think of at least two channels: (1) a direct influence on wages in the marketplace, i.e. through a direct pricing of the traits; and (2) an indirect channel through educational attainment. The pricing of traits might occur early or late in a person’s working life. Also, the price might be a function of the person’s educational attainment. If psychological traits such as IQ alter the probability of obtaining higher education, and if there is a positive return to education, the traits alter a person’s lifetime earnings potential indirectly.

After presenting the total effects of IQ and personality traits on the life-time earnings of the Terman men and women (Section 3.1), and discussing the estimation procedures Section 3.2, the two channels are examined. Section 3.3 analyzes the direct effect, or the prices of traits, by education level, for men and women. Section 3.4 shows the indirect effect by asking how educational sorting is a function of psychological traits. The rate of return to education, which determines the magnitude of the indirect effect, is examined in Section 3.5

3.1 The Effect of Personality and IQ on Total Lifetime Earnings

The total effects of personality and IQ on lifetime earnings\textsuperscript{16} of men and women in the Terman sample are shown in Table 2. Personality traits and IQ clearly play a large role in determining lifetime earnings of males. \textit{Ceteris paribus}, lifetime earnings are higher if the men are more conscientious and extraverted, and if they are less agreeable. Earnings are

\textsuperscript{16}Lifetime earnings are the sum of each individual’s earnings from age 18 to age 75; for women, we also consider the sum of their husbands’ earnings and the resulting family earnings. Family earnings for the males can not be evaluated because the men in the sample were never asked to report their spouse’s earnings, whereas the females were regularly asked about their husband’s income.
also increasing in IQ. It is remarkable that even in this sample, where IQs are restricted to the top range, IQ is still positively and significantly associated with lifetime earnings. An increase of IQ by 15 points would increase discounted lifetime earnings by 210 thousand dollars, controlling for education and background variables. 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. Even at the high end of the ability distribution, additional IQ has meaningful consequences.

Women’s own earnings (column (2)) are also significantly increased by Conscientiousness; but for them lifetime earnings are not higher if they are more extraverted. Instead, they are higher for women who score higher on Openness to experience, and lower on Neuroticism. More extraverted women have higher lifetime earnings from their spouse (column (3)). Since for Neuroticism and Openness to experience, the lifetime effects on own and spouse’s earnings have opposite signs, women’s family earnings (column (4)) are in fact only a significant function of Conscientiousness and Extraversion. Generally, the effects of personality traits on life-time earnings are much smaller for women.

3.2 Estimation Procedure

All effects of education and personality traits on earnings are identified using the rich set of background and psychological variables at our disposal, in order to correct for any selection problems into educational status. Thus “selection on observables” (Heckman and Robb, 1985) or a “matching” assumption are invoked. The specific implementation based on this assumption is Ordinary Least Squares.\footnote{The results are not a function of the linearity — other models, including a nonparametric one, yield the same effects of education and personality traits. The description of these, and a comparison of the results, is in the Web Appendix Section C.8.}

We estimate the following linear specification for earnings at age $t$, for persons with
Table 2: The Influence of Personality and IQ on Lifetime Earnings

<table>
<thead>
<tr>
<th></th>
<th>Men</th>
<th>Women</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Own Earn.</td>
<td>Own Earn.</td>
<td>Husband’s Family</td>
<td></td>
</tr>
<tr>
<td>IQ</td>
<td>186.1*</td>
<td>-3.7</td>
<td>-46.4</td>
<td>-56.3</td>
</tr>
<tr>
<td></td>
<td>(0.07)</td>
<td>(0.48)</td>
<td>(0.35)</td>
<td>(0.34)</td>
</tr>
<tr>
<td>Openness</td>
<td>-113.2</td>
<td>101.5*</td>
<td>-200.9</td>
<td>-118.5</td>
</tr>
<tr>
<td></td>
<td>(0.22)</td>
<td>(0.08)</td>
<td>(0.18)</td>
<td>(0.28)</td>
</tr>
<tr>
<td>Conscientiousness</td>
<td>577.5***</td>
<td>153.3**</td>
<td>81.2</td>
<td>223.2*</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.01)</td>
<td>(0.33)</td>
<td>(0.09)</td>
</tr>
<tr>
<td>Extraversion</td>
<td>510.7***</td>
<td>-69.3</td>
<td>266.5</td>
<td>241.2</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.16)</td>
<td>(0.10)</td>
<td>(0.12)</td>
</tr>
<tr>
<td>Agreeableness</td>
<td>-304.9**</td>
<td>-55.6</td>
<td>176.5</td>
<td>94.1</td>
</tr>
<tr>
<td></td>
<td>(0.05)</td>
<td>(0.25)</td>
<td>(0.17)</td>
<td>(0.29)</td>
</tr>
<tr>
<td>Neuroticism</td>
<td>-1.9</td>
<td>-84.0*</td>
<td>110.5</td>
<td>22.8</td>
</tr>
<tr>
<td></td>
<td>(0.46)</td>
<td>(0.07)</td>
<td>(0.21)</td>
<td>(0.41)</td>
</tr>
<tr>
<td>Mean of Lifetime Earnings</td>
<td>3391</td>
<td>696</td>
<td>2098</td>
<td>2807</td>
</tr>
<tr>
<td>Observations</td>
<td>595</td>
<td>422</td>
<td>422</td>
<td>422</td>
</tr>
</tbody>
</table>

Notes: p-values in parentheses, *p < .1, **p < .05, ***p < .01.

The dependent variable is total lifetime earnings in thousand US Dollars from age 18 to 75, in thousand US Dollars of 2010, after tuition. The estimates show the coefficients from a regression that includes the standard covariates for the treatment effect estimation, but not education. The coefficients on personality traits have been adjusted for attenuation bias, as described in Section 3.2, and represent the effects of a one-standard deviation increase in the trait.
schooling level $j$, $Y_{j,t}$:

$$Y_{j,t} = X_t \beta_t + \theta \delta_{j,t} + D_{j,t} \nu_{t,j} + \rho_{t,j}, \quad t = 1, \ldots, T; j = 1, \ldots, J,$$

(1)

where $X_t$ is a vector of background variables, $\theta$ is a vector of traits (IQ and personality factors), $D_{j,t}$ is a dummy variable that equals 1 if a person is at schooling level $j$ (of $J$ possible schooling levels) at age $t$, defined in a mutually exclusive fashion (so $\sum_{j=1}^{J} D_{j,t} = 1$ for all $t$) and $\nu_{t,j}$ is the average effect of schooling. Equation (1) is estimated separately for men and women. In fact, as the results will show, the null hypothesis that $\delta_{j,t} = \delta_j$ for all $t$ can not always be rejected at common significance levels for the $t$ individually. Therefore, the $\delta_{j,t}$ are subsequently also estimated as constant across education levels. The exact link to the standard Roy model of counterfactuals is presented in Web Appendix B.

The psychological traits are summarized by factor scores, which are estimated using the Bartlett method, based on a standard linear factor model. Since the estimation of factor scores introduces error, the naive least squares estimates suffer from attenuation bias. They can be corrected for estimation error using the method of Croon (2002). All standard errors are bootstrapped accounting for the fact that the predictions are based on an estimation of the measurement system. In all estimations, unless otherwise noted, condition on personality traits (using extracted factors), IQ and family background variables discussed in the preceding section.

Note that we allow explicitly for the effect of personality traits and IQ, $\delta_{j,t}$, to vary by educational level. This means that the treatment effect of education is allowed to be heterogeneous, or in other words that there is an interaction between the education and

---

18 See Bartlett (1937); Thomson (1938). The often-used regression method based on Thurstone (1935) results in estimates of the factor scores which are biased with respect to their means, and more importantly for the error correction method we are interested in, their covariance structure.

19 For applications of Croon’s method, see Heckman, Malofeeva, Pinto, and Savelyev (2011) and Heckman, Schennach, and Williams (2011).

20 It is standard practice to bootstrap the standard errors or estimate them with other Monte Carlo methods (Bolck et al., 2004). Even though Hoshino and Shigemasu (2008) have presented a formula that eliminates the need for simulations, their proposed solution is only valid in applications with large numbers of observations and measurements.
traits in their effect on earnings. As the next section will show, this is an important aspect for the Terman men.

3.3 The Direct Effects of Personality Traits and IQ on Earnings

Now consider the first channel of influence of psychological traits on lifetime earnings — the direct effect they have on earnings, holding constant educational attainment. How are psychological traits priced in the marketplace? When do gains or losses occur? And is the pricing of traits independent of the educational attainment?

We find that some traits are highly rewarded in the marketplace, and that the largest effects (both positive and negative) arise later in the working life. And the lifetime effects of personality traits are indeed a function of educational attainment, thus altering the payoff from education depending on a person’s personality profile.

An overview is provided by Table 3, which shows the direct effects on total lifetime earnings. For this table, Eq. (1) was estimated on $Y_{iT} = \sum_{t=18}^{75} Y_{it}$. The different levels of education, $j$, are “Bachelor’s or less” and “Master’s or more.”

For men, as in the total effect, the direct effect of IQ is positive and statistically significantly different from zero. Therefore, the lifetime effect of IQ on earnings is not only driven by higher educational attainment associated with higher IQ, but also through a direct impact on earnings. IQ impacts earnings similarly across education levels. Conscientiousness, and Extraversion, are associated with higher earnings regardless of education level. The reward to being more conscientious and extraverted, however, is greater for more highly educated men. This difference is statistically significant with p-values of 6% and 1%, respectively. More agreeable men earn less, especially so if they are in the highly educated category of having a Master’s or a doctorate degree. Interestingly, more neurotic men seem to earn more when they are in this education category. While the point estimate is not significant, the difference to the point estimate for less educated men is significant.

Women’s IQ is strongly negatively related to lifetime earnings for women with at most
a Bachelor’s degree, but not for the most highly educated women. The difference is highly significant too. Women of this highly select sample who obtained at most a Bachelor’s degree have lower earnings husbands when their IQs are in the highest ranges as opposed to “just above 140.” This surprising negative effect, however, is limited to women who did not achieve the highest educational attainments. Apparently, women with a Master’s or more are able to avoid this wage penalty to higher IQs. Women with high scores in Openness to experience benefit from this trait, either in terms of own earnings (Master’s or more) or family earnings (Bachelor’s or less), whereas it is insignificant for men. As for men, Conscientiousness has a positive effect on earnings, but only so for women with at most a Bachelor’s degree. The effect on the more highly educated women is inconclusive. So are the effects of Extraversion and Agreeableness. Surprisingly, women with less education seem to have higher lifetime earnings if they score higher on Neuroticism.

The bottom half of Table 3 highlights the importance of accounting for heterogeneous effects of the personality traits by educational attainment. For men, Conscientiousness, Extraversion, and Neuroticism have statistically significantly different effects on lifetime earnings. For women, education matters for the effects of IQ, Openness, Conscientiousness, and Extraversion. Standard analyses without interactions ignore this heterogeneity and over- or under-state the effects of these traits when considering the average impacts only.
3.3.1 Men

Figure 2 (page 18) presents the effects of personality traits and IQ on lifetime earnings of the Terman males, by education. This means the $\delta_{j,t}$ are plotted over time $t$ for two $j$, either “Bachelor’s degree or less,” or “Master’s or doctoral degree.” While the effects vary by education, the graphs reveal that the direct effects, when estimated age-by-age, are not statistically significantly different from each other.\footnote{The Appendix shows the difference between the coefficients and the associated 95\% confidence bands of the difference, which include zero.}

Since the signs of the effects are equal across the education levels, except for Neuroticism, a sparser model that does not estimate the $\delta_{j,t}$ by education level is a good benchmark. In the common coefficient model, all $\delta_{j,t}$ are forced to $\delta_{j,t} = \delta_{j}$:

$$Y_{j,t} = X_t \beta_t + \theta \delta_t + D_{j,t} \nu_t + \rho_{t,j}, \quad t = 1, \ldots, T; j = 1, \ldots, J,$$  \hspace{1cm} (2)

Figure 3 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. Conscientiousness is also 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 longer hours. This would link back to the literature on the role Conscientiousness plays in health (Lodi-Smith et al., 2010). It has been shown that more conscientious individuals live longer (Friedman et al., 1993b; Weiss and Costa, 2005). They are less likely to experience the chronic illnesses which 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 precisely estimated - the lifetime earnings effect are more negative (and only significant) for more highly educated men. By combining coefficient, this impact is lost. Müller and Plug (2004) find that antagonistic (or less agreeable) men earn more - in this sense, the Terman findings are similar. Openness never seems to have a positive effect on earnings, but it is not statistically precisely estimated, and even the effect on total lifetime earnings is not statistically significantly different from zero. 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. The Terman study is a case study of a group of persons with similar IQs that also provides a direct IQ score. Controlling for IQ, Openness does not have a clear effect on earnings. Finally, we can conclude that **Neuroticism** does not affect earnings in the Terman sample.

The effects of personality traits on earnings are very small in the early years of the working life, until about age 30. Therefore, having access to data that combines measures of personality traits and IQ with long follow-up is essential. One can only describe the effects of these traits in a satisfying manner with earnings measures that extend well into the prime working years. The effects of Conscientiousness, Extraversion, and IQ only materialize after the thirties. 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.  

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22 Interestingly, these authors show that Conscientiousness is not statistically significantly different from zero for men in the Wisconsin Longitudinal Study; whereas the measure in Terman is clearly significant.

23 A caveat about causality is in order. In contrast to the estimated effect of education on earnings, which we can interpret 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 actually the result of previous labor market experience. Then, the 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).

We follow 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 aged 25–35. While claims of
causality have to be guarded, we do think the results are showing earnings gains due to personality and IQ
for two reasons. First, we perform a robustness analysis to test whether the 1940 measures of personality
traits are a function of early labor market success. We extract the personality factors 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. Second, note
that the strongest associations of the personality traits with earnings arise later in the working life. Under
reverse causality, one would expect them to be strongest early on since the early labor market success (i.e.
high wages) would cause the personality trait. Since the opposite is observed, even for the traits measured
in 1940, the argument that our results are driven by reverse causality is weaker.
### Table 3: The Direct Effects of Personality and IQ on Lifetime Earnings by Education

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

<table>
<thead>
<tr>
<th></th>
<th>Men</th>
<th>Women</th>
<th></th>
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</thead>
<tbody>
<tr>
<td></td>
<td>(1) Own Earn.</td>
<td>(2) Own Earn.</td>
<td>(3) Husband’s</td>
<td>(4) Family</td>
</tr>
<tr>
<td>IQ</td>
<td>3.2 (0.42)</td>
<td>-10.9 (0.46)</td>
<td>-565.4** (0.01)</td>
<td>-566.9*** (0.00)</td>
</tr>
<tr>
<td>Openness</td>
<td>-71.4 (0.37)</td>
<td>43.7 (0.37)</td>
<td>722.7* (0.05)</td>
<td>738.8** (0.02)</td>
</tr>
<tr>
<td>Conscientiousness</td>
<td>259.8* (0.06)</td>
<td>192.7* (0.07)</td>
<td>-447.2 (0.12)</td>
<td>-269.2 (0.19)</td>
</tr>
<tr>
<td>Extraversion</td>
<td>427.5** (0.01)</td>
<td>-114.3 (0.29)</td>
<td>-740.3** (0.04)</td>
<td>-819.8** (0.01)</td>
</tr>
<tr>
<td>Agreeableness</td>
<td>-307.8 (0.17)</td>
<td>89.8 (0.34)</td>
<td>-516.7 (0.15)</td>
<td>-446.0 (0.21)</td>
</tr>
<tr>
<td>Neuroticism</td>
<td>417.8* (0.08)</td>
<td>-157.4 (0.18)</td>
<td>-111.7 (0.39)</td>
<td>-208.7 (0.28)</td>
</tr>
</tbody>
</table>

**Notes:** p-values in parentheses, *p < .1, **p < .05, ***p < .01. The dependent variable is total lifetime earnings in thousand US Dollars from age 18 to 75. Shown are standardized coefficients from a regression that includes the standard covariates for the treatment effect estimation, adjusted for attenuation bias (see Section 3.2). The bottom table shows the differences of direct effects between education levels and the associated bootstrap p-values from 200 draws.
Figure 2: The Direct Effect of Personality and IQ on Lifetime Earnings, Men

Notes: Standardized coefficients $\delta_{t,j}$ from equation (1), on earnings after tuition. The shaded areas are standard 95%-confidence bands from a bootstrap with 200 draws.
**Figure 3:** The Direct Effect of Personality and IQ on Lifetime Earnings, Men, Common Coefficient

<table>
<thead>
<tr>
<th>IQ</th>
<th>Conscientiousness</th>
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<tr>
<th>Extraversion</th>
<th>Neuroticism</th>
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<table>
<thead>
<tr>
<th>Openness</th>
<th>Agreeableness</th>
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**Notes:** Standardized coefficients $\delta_t$ from equation (2), on earnings after tuition. The shaded areas are standard 95%-confidence bands from a bootstrap with 200 draws.
3.3.2 Women

For women, the estimates of the effects of personality traits and IQ on earnings are generally more noisy than for men. There are at least three reasons for this: For women, we are analyzing family earnings, which are constituted of the husband’s earnings, and own earnings. The same trait may have different effects on these two types of earnings. Secondly, there are fewer women than men in the Terman sample, so for the same number of covariates the estimates are less precisely determined. Thirdly, in the case of women, the few with a doctorate degree are so particular, and have very different earnings streams, that they can almost be considered outliers.

Figure 4 shows the direct effects of personality traits on the combined earnings of Terman females and their husbands.\(^{24}\) The most striking feature of the effects are how large the confidence bands are for women with a doctorate or Master’s degree (in purple), whereas they are more reasonable for the less educated women.\(^{25}\) Only 28\% of women in our sample are in this high education category, or 120 women, leading to the noisy estimates. When looking at the differences between effects by education level, they clearly exist in levels, but the confidence bands overlap largely. Remember, however, that the differences are statistically significant for lifetime earnings in IQ, Openness, and Extraversion.

While it is clear that since the effects are so noisy that one should not be confident about their size or sign, knowing their constituents is of interest. In particular, since we know that the direct effect of Extraversion on lifetime earnings, for example, are significantly different between women with a Master’s degree or higher as opposed to women with a Bachelor’s degree or less, it is important to see whether the difference is driven by the same components having different effects, or by different components. Figures 5 and 6 show, in blue or pink color, the stacked effects of traits on the husband’s or own earnings, that together make up

\(^{24}\)The full set of figures also for own and husband’s earnings separately can be found in the Web Appendix C.

\(^{25}\)Note that in the case of women, the common coefficient model 2 does not yield estimates of the direct effects that are statistically significantly different from zero age-by-age, as was the case for men in Fig. 3, even if we exclude the women with a doctorate degree from the estimation.
family earnings. And indeed, the overall positive effect of extraversion for women with a Bachelor’s or less is almost entirely driven by the effect of extraversion on husbands’ earnings. More extraverted women marry more frequently, or more higher earning husbands. In the case of women with a Master’s degree or more, highly extraverted women have men who are earning slightly less, and they also tend to earn less themselves. Individually, these two effects are not statistically significantly different from zero, but taken together they are significantly different over a lifetime (Table 3), as is the positive effect of extraversion for the less highly educated women.

Openness is the mirror image of Extraversion; highly educated women benefit from having intellectual taste and being open to new experiences, whereas women with at most a Bachelor’s have lower earnings when they score higher on this trait.

In general, the pink slices representing the effects of personality and IQ on women’s own earnings are very small. A likely explanation for the lack of association between own earnings and the Terman females’ traits is that fertility and the probability of marriage are not significantly associated with personality traits within this sample. Since much of the labor market behavior can be attributed to their family status, it is not surprising to find that traits and IQ do not influence the women’s earnings in a meaningful way. The lack of effects is not only driven by zero earnings of many housewives: when I estimate these effects only on a subsample of women who have earnings of ten thousand dollars per year or more for at least 20 out of the 48 working years between age 18 and 65, the effects are still very small and not statistically significantly different from zero.

Figures Figs. 5 and 6 demonstrate how educational attainment alters the effect certain personality traits have on the earnings they receive through their husbands - IQ, Extraversion, and Openness affect their potential in the marriage market differently depending on whether they have a Bachelor’s or less, or a Master’s or doctorate degree.

\footnote{Tables not shown but available upon request.}
**Figure 4:** The Direct Effect of Personality and IQ on Lifetime Earnings, Women

**Notes:** Standardized coefficients $\delta_{t,j}$ from equation (1), on family earnings after tuition. The shaded areas are standard 95%-confidence bands from a bootstrap with 200 draws.
Figure 5: The Direct Effect of Personality and IQ on Lifetime Earnings, Women with a Bachelor’s degree or less

Notes: Standardized coefficients $\delta_{j,t}$ from equation (1), for $j = \text{Bachelor’s degree or less}$, on three earnings types: women’s own earnings (pink shade), their husband’s earnings (blue shade) and the combined family earnings after tuition (black solid line, with a 95% confidence band, shaded gray).
Figure 6: The Direct Effect of Personality and IQ on Lifetime Earnings, Women with a Master’s or Doctorate degree

Notes: Standardized coefficients $\delta_{j,t}$ from equation (1), for $j = \text{Master’s degree or more}$, on three earnings types: women’s own earnings (pink shade), their husband’s earnings (blue shade) and the combined family earnings after tuition (black solid line, with a 95% confidence band, shaded gray).
3.4 The Effects of Psychological Traits on Educational Attainment

An emerging literature shows that psychological traits can be linked to educational attainment. 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 (correlation) 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, as IQ is not controlled for in these studies.

Based on a generalized ordered logit model of education choice,\(^\text{27}\) presented in Table 4, 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 slightly 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. For males, Conscientiousness positively affects the probability of passing the thresholds of Bachelor’s degree, Master’s degree, and Doctorate (see Table 4). For females, it significantly increases the chance of obtaining a master’s degree or higher. Thus, at each of these thresholds, more conscientious men and women are less likely to remain in any of the education levels that are lower, in comparison to the threshold or a higher education level. Conscientiousness likely enhances education through lowering the psychic

\(^{27}\)The generalized ordered logit model (e.g., Williams, 2006) is a collection of binary logit models for each of \(N-1\) thresholds of \(N\) ordered choices. In this paper, the four thresholds are the following: (1) some college, (2) Bachelor’s, (3) Master’s, and (4) Doctorate. For instance, a binary logit model for the threshold “Bachelor’s” estimates the choice of Bachelor’s degree or above vs. some college education or high school diploma. The generalized ordered logit model is equivalent to the ordered logit model when the coefficients for each regressor are restricted to be the same for all binary logits within the generalized model. Equality of these coefficients is called the parallel regression assumption, which we test and reject for the Terman data. Thus, the more parsimonious ordered logit model should not be used. Another alternative model, the multinomial logit, relies on the independence of irrelevant alternatives assumption, which is not supported by the Terman data.
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 thought of as being associated with lower discount rates for deferred gains. Finally, 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. Men with a higher Openness score are more likely to obtain a bachelor’s degree or more, and women are more likely to achieve a master’s or doctorate degree. This result helps to resolve the uncertainty in the literature about the role of Openness in predicting educational attainment. Openness positively affects education even conditioning on IQ.

Apart from Conscientiousness and Openness, the effects of other psychological traits differ by gender. This might reflect the different role that education played for the females of this cohort compared to the role of education for males. 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. Yet, the result is less puzzling when we remember two facts: All Terman women had an exceptionally high IQ, so we are not comparing low-IQ women to high-IQ women. Also, the threshold in question is very high and only few women of this cohort obtained a doctorate degree (6%). 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.\(^{28}\)

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. The associations for Terman males diverge from these pooled samples.

\(^{28}\)The share of Terman males who obtained a Doctorate is 27%.
The effect of Extraversion on educational choice is negative for females. One expects this negative effect (socializing takes time away from studies), and it has indeed been found in previous studies for representative samples of men and women. More extraverted Terman women are less likely to pass the thresholds of a bachelor’s degree as well as a doctorate degree. For Terman men, extraversion has no significant effect on educational attainment, which is not what other researchers find.

Finally, 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 (Almlund et al., 2011; Baron and Cobb-Clark, 2010). Neuroticism increases the likelihood of choosing at least a bachelor’s degree for men.

Thus, traits influence education, but their effects depend on gender as well as the educational margin considered. The educational sorting of Terman females by psychological traits is similar to what other researchers have found based on representative datasets, where men and women were pooled together. It would be interesting to contrast our findings on Extraversion, Agreeableness, and Neuroticism to results from representative datasets where the associations are broken out by gender as well. Conscientiousness and Openness have a similar role in the Terman sample for both men and women: they increase the probability of choosing higher educational levels. This is in line with previous results. Furthermore, we can establish that Openness has a positive role in enhancing education that is independent of IQ.

29The reverse of Neuroticism is Emotional Stability, and in this text we denote with these the two end points of the scale. This differs from the practice in the current psychological literature, where Neuroticism is sometimes reverse-coded so that by high Neuroticism the researchers actually denote high Emotional Stability, or “positive Neuroticism.”
Table 4: The Role of Psychological Traits on Education, Generalized Ordered Logit Model

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

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 coefficients for “Some College,” for example, show the effect of personality traits on the likelihood of remaining a high school graduate versus attending college and any higher educational attainment. The estimates in column “Bachelor’s” corresponds to the binary choice between high school or some college education versus a bachelor’s degree up to a doctorate.
The estimates condition on the standard set of background controls which are listed in Table 1. Asterisks denote statistical significance based on a two-sided asymptotic test; * p < .1, ** p < .05, *** p < .01.
3.5 The Rate of Return to Schooling

Now that we have 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. The rate of return to education is computed from the estimates of the earnings equations (Equation (1) for ages $t = 18, ..., 75$). Because we have complete life-cycle earnings data, we do not have to impose the standard procedures developed by Becker and Chiswick (1966) and Mincer (1974) to use cross sectional data to estimate life-cycle rates of return.\footnote{Heckman et al. (2006, 2008) review the literature which is based on this approach.} Indeed, we test and reject the adequacy of the widely-used Mincer specification. Instead of relying on years of schooling as our outcome variable, we contrast different levels of education in pairwise comparisons. This yields a richer picture of the different trade-offs that individuals face when choosing one education level over another.

Furthermore, we show a drastic departure from the traditional rate-of-return analysis, due to the interactions we have established in Section 3.3. The rate of return to education is significantly higher for men who are highly extroverted, conscientious, and who score low on Openness and emotional stability.

We first discuss what the Mincer estimates would be for the Terman sample, and then contrast it to pairwise internal rates of return for males. Then we show by how much the rate of return varies by personality traits and IQ. Finally, we turn to the effect of education on women’s earnings, decomposing the effects on own earnings and on their husbands’ earnings. All estimates control for the variables of Table 1.

3.5.1 The Mincer Coefficient

Most rates of return that are presented 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 combined earnings with their husbands it is only 3.6%.\textsuperscript{31} We will see that these rates are masking a lot of different returns that can be observed for the different education levels.

3.5.2 The IRR for Men

The average treatment effect of education level $j$ vs $k$ at each age $t$ corresponds to $\nu_{t,j} - \nu_{t,k}$ from Eq. (1). Since the treatment effect of education is a function of the psychological traits, as shown in Section 3.3, we report here the average treatment effect for men with average scores on all personality traits and average IQ of the sample.\textsuperscript{32}

The pairwise estimates of the average treatment effects are plotted in Fig. 7. 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 effect of education is substantial during the prime working years, a standard result in the literature (see Becker, 1964).

The IRRs and Net Present Values (NPVs) corresponding to the estimated average effects are listed in each sub-graph.\textsuperscript{33} In principle, an IRR should be compared to the market interest rate to determine the optimality of schooling.\textsuperscript{34} This comparison ignores the dynamic aspect

\textsuperscript{31}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 and experience, and its square, as well as the set of psychological traits and background variables as in our standard estimation.

\textsuperscript{32}Note that in the limit, the average treatment effect of education as estimated from Eq. (1) is equal to the estimates from Eq. (2), as the personality traits and IQ are normalized to have mean zero.

\textsuperscript{33}The IRR are computed in the traditional fashion suggested by Becker (1964). Even though Becker (1964) and Heckman et al. (2006, 2008) used after-tax earnings, other authors tend to use pre-tax earnings. Therefore, the results here are for earnings after tuition, but before tax. The corresponding figures and tables for after-tax earnings can be found in Web Appendix C, Section C.5.

\textsuperscript{34}The “nonlinear” pattern of some of the pairwise IRRs is not as counterintuitive as it might seem. For example, if for males the return of a master’s degree versus a bachelor’s degree is almost zero at -1.1%, and the IRR of a doctorate degree versus a master’s is 11.5%, one might initially expect the IRR of a doctorate versus a bachelor’s to be similar to 11%. The graphs of pairwise treatment effects are helpful for an intuitive understanding. The IRR of a doctorate over a bachelor’s is the result of a sizeable positive treatment effect
of schooling and the sequential revelation of uncertainty.\textsuperscript{35} Our analysis is explicitly \textit{ex-post} and considers rates of return in a static setting.

The pairwise treatment effects are clearly different from each other and can not 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 $349,677 over a lifetime, if the difference in earnings is discounted at 3%. The corresponding IRR is 11.8%. 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.\textsuperscript{36}

Even though the category of “some college” is a rather heterogeneous one, attending college (without obtaining a degree) increases the Terman men’s earnings once we hold their traits constant. The levels of the average treatment effects are similar to those of a bachelor’s degree, with a slightly smaller investment as well as a lower return later in life. This leads to an IRR which is still relatively high at 7.8%.

The rates of return for a master’s degree or a doctoral degree in comparison to a high school diploma are lower—because the investment periods for obtaining these degrees are longer. The IRRs are 8.1% 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 ($475,022 vs $279,808).

\textsuperscript{35}See for example \textcite{heckman2006} 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 \textcite{heckman2008}.

\textsuperscript{36}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%.
The absolute treatment effects of incremental improvements, such as bachelor’s degree over “some college”, or doctorate over master’s, are relatively small. But since these small gains can be had at an even smaller cost, the resulting rates of returns are substantial (15.0% and 11.9%).

In comparison to having a bachelor’s degree, having a master’s degree has almost no return, and the treatment effect is negative for many years. The IRR is actually negative at -2.4%. For the person with average levels of all psychological traits, obtaining a doctoral degree over a bachelor’s degree increases increase lifetime earnings, but only by an NPV of $124.346). 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.
Figure 7: Pairwise Average Treatment Effects on Earnings, Males

<table>
<thead>
<tr>
<th></th>
<th>Some College vs High School</th>
<th>Bachelor’s vs High School</th>
<th>Master’s vs High School</th>
<th>Doctorate vs High School</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>IRR</strong></td>
<td>8.1</td>
<td>12.2</td>
<td>8.5</td>
<td>9.1</td>
</tr>
<tr>
<td><strong>CI</strong></td>
<td>[-19.0, 16.1]</td>
<td>[5.5, 17.4]</td>
<td>[4.0, 12.4]</td>
<td>[5.6, 11.8]</td>
</tr>
<tr>
<td><strong>NPV</strong></td>
<td>73.2</td>
<td>359.0</td>
<td>300.1</td>
<td>475.9</td>
</tr>
<tr>
<td></td>
<td>[-170, 302]</td>
<td>[100, 517]</td>
<td>[55, 517]</td>
<td>[255, 710]</td>
</tr>
<tr>
<td></td>
<td>15.3</td>
<td>8.7</td>
<td>9.4</td>
<td>11.5</td>
</tr>
<tr>
<td></td>
<td>[4.2, 23.6]</td>
<td>[4.5, 14.5]</td>
<td>[6.0, 13.1]</td>
<td>[-2.0, 22.4]</td>
</tr>
<tr>
<td></td>
<td>-1.1</td>
<td>5.8</td>
<td>-57.2</td>
<td>118.7</td>
</tr>
<tr>
<td></td>
<td>[-12.0, 49.6]</td>
<td>[1.7, 12.4]</td>
<td>[-252, 175]</td>
<td>[-31, 371]</td>
</tr>
<tr>
<td></td>
<td>11.5</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>[-2.0, 22.4]</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: Treatment effects from Eq. (2), evaluated for a person with average personality traits, and 95% confidence bands from 200 bootstrap draws. Earnings are annual earnings after tuition in 2010 U.S. Dollars. The covariates are IQ, factor scores for personality traits, parental background, family environment, early childhood health and 1922 health information, and controls for WWII and cohort.
Figure 7 continued: Pairwise Treatment Effects on Earnings, Males

Notes: Treatment effects from Eq. (2) and 95% confidence bands from 200 bootstrap draws. Earnings are average annual earnings, in 2010 U.S. Dollars. The covariates are IQ, factor scores for Openness, Conscientiousness, Agreeableness, Extraversion, and Neuroticism, parental background, family environment, early childhood health and 1922 health information, and controls for WWII and cohort. See the Web Appendix for information on constructing the earnings profiles, and the marriage history, from the raw data.
3.5.3 The IRR for Women

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 remunerated activity, despite their extraordinary abilities and talents.

A woman was more likely to be in gainful employment and less likely to be married if she had obtained higher levels of education than a Bachelor’s degree, as one can see in Fig. 8. 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. A richer model of decision making is required for women than for men in order to make causal statements.

Since so many women of this cohort were mainly housewives and did not earn a market wage, they might gain through education by finding a better match, a husband with higher educational achievement, and thus increase their potential family earnings. In fact, the correlation of the Terman women’s years of education with their husband’s (for those who are married) is .36. We decompose the treatment effect of education for women into its effect on their own earnings and on their husband’s earnings (which is the effect through marriage). The combined effect will be the sum of the two, or the treatment effect of education on family earnings. The decomposition is illustrated graphically in Fig. 9.

The gains through marriage, shown in blue, are positive for women with a bachelor’s
Figure 8: 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.
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. In the case of women with a Master’s degree, the negative effect is clearly related to lower probability of being married - as Fig. 8 shows. A woman’s propensity to be married is much lower for women with a master’s as opposed to a bachelor’s degree or high school diploma. 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, when they were married their husbands had higher-than-average earnings, so overall the impact of their high education on the returns to marriage are not statistically different from zero. Figure 10 explores these different effects: It shows two counterfactual treatment effects of education on the women’s gains through marriage. In green, the solid line shows the effect of education on the quality of matches. It assumes that all women in the sample were married (marriage propensity of 1), and education is allowed to affect only husband’s earnings. 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, represented by the purple dashed line, assumes that once married, the earnings through husbands were equal. Education affects the marriage propensity only. Clearly, marriage prospects 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, as seen in the blue shade in Fig. 9.

Women improved their own earnings by obtaining post-graduate education (see the pink shaded areas). The treatment effect of a master’s degree is positive but remains small and is not statistically significantly different from zero. For women with a doctorate degree, the returns to education are substantial, and even higher in absolute levels and 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. Even though family earnings are not precisely estimated age-by-age, the treatment effect on own earnings is (not shown). Clearly, 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. Unfortunately, since there are only 24 women in the sample who obtained a doctoral degree,\(^{37}\) the treatment effects are relatively imprecisely determined.

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. For women with a master’s, the rate of return is in fact negative, because the return through own earnings is not enough to offset the losses in the marriage market.\(^{38}\)

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.

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\(^{37}\)There were 26 women in the overall sample, but we restrict the treatment effect analysis to those observations with complete earnings histories.

\(^{38}\)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 also there might simply not exist a rate of return that would set the net present value of this investment to zero.
Figure 9: Pairwise Treatment Effects on Earnings and Decomposition, Females

Notes: Treatment effects from the estimation equation (1), on three measures of annual earnings in 2010 U.S. Dollars: Terman female’s earnings (pink area), her husband’s earnings (blue area), and the combined family earnings (solid black line, grey area is the 95% confidence band from 200 bootstrap draws).
Figure 10: Counterfactual Effects of Education on Earnings through Husbands

Notes: Counterfactual average treatment effects from the estimation equation (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.
4 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, their effects on lifetime earnings are a function of educational attainment. 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 - in an age-by-age estimation, they may fail to be statistically significant.

Psychological traits are priced directly in the marketplace for men, but not for women. 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 can be sizeable. For women at education levels below the doctoral level, the rates of return are low. Women with a college education gain through sorting in the marriage market. Women with a doctorate degree have very high earnings on their own, and their rates of return are even higher than those of men.
References


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