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Psychological Skills, Education, and Longevity of High-Ability Individuals

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Abstract

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A version of this paper was presented to the Annual Meeting of the American Economic Association in Chicago; the Health Economics Workshop at the NBER Summer Institute; the European Economic Association and Econometric Society Annual European Meeting in Gothenburg, Sweden; the Health Economics Workshop and the Labor Group Seminar at the University of Chicago; Applied Microeconomics seminar at the University of North Carolina; the Institute on Health Economics, Health Behaviors, and Disparities at Cornell University; Economics seminar of the Andrew Young School of Policy Studies, Georgia State University; University of Houston and Rice University Empirical Micro seminar; RAND Labor and Population Seminar in Santa-Monica; the Quantitative Methods Brown Bag at the Department of Psychology and Human Development at Peabody College, Vanderbilt University; Departmental Seminar in Economics at Vanderbilt University; the Applied Microeconomics Seminar at Vanderbilt Law School; David Eccles School of Business research seminar, University of Utah; and the Upjohn Institute for Employment Research seminar. I thank participants of these meetings for useful suggestions and stimulating discussions. I am grateful to Gary Becker, Gabriella Conti, Miriam Gensowski, Mike Grossman, Tim Kautz, Don Kenkel, Adriana Lleras-Muney, Willard Manning, David Meltzer, R´emi Piatek, Kegon Tan, Ben Ward, Ben Williams, and especially Jim Heckman for productive comments; to Mihir Gandhi, Kai Hong, and Ivana Stosic for their excellent research assistance over different stages of this long project; to Keith Dent, Son Nghiem, and Cody Vaughn for great help during their summer internships at Vanderbilt; and to the Economics Research Center at the University of Chicago for its support of early versions of this work. I thank John Spraul for his excellent proofreading. The Terman data are provided by the Interuniversity Consortium for Political and Social Research Ann Arbor, MI. An early version of this paper was supported by the Merck Quantitative Science Graduate Fellowship in Health Economics. The paper also benefited from the financial support of the Douglas W. Grey Faculty Research Fund in Economics. The views expressed in this paper are those of the author and may not coincide with those of the funders. Supplementary materials may be retrieved from https://my.vanderbilt.edu/petersavelyev/2012/01/web-appxterman.
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Working paper

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Key words: longevity, survival function, life expectancy, value of longevity, post-compulsory education, IQ, personality skills, Big Five, average treatment effect, Terman Data of Children with High Ability, gender difference

JEL codes: C41, D91, I12

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1 Introduction

It is well documented in the literature that longevity is primarily produced through *health behaviors* such as avoiding smoking tobacco and following a healthy diet (e.g., Phelps, 2013).[1] Preferences for these behaviors are formed as a result of a complex process of human development, implying that determinants of human development can be expected to affect longevity. The emerging literature in economics of human development suggests that we can expect to find such determinants among cognitive and personality skills, as well as among investments in education (Almlund et al., 2011). In this paper I find substantial effects of cognitive skills, personality skills, and education on longevity. I also provide evidence in favor of interpreting the estimated effects as causal (see Figure 1 for a scheme of the estimated model).

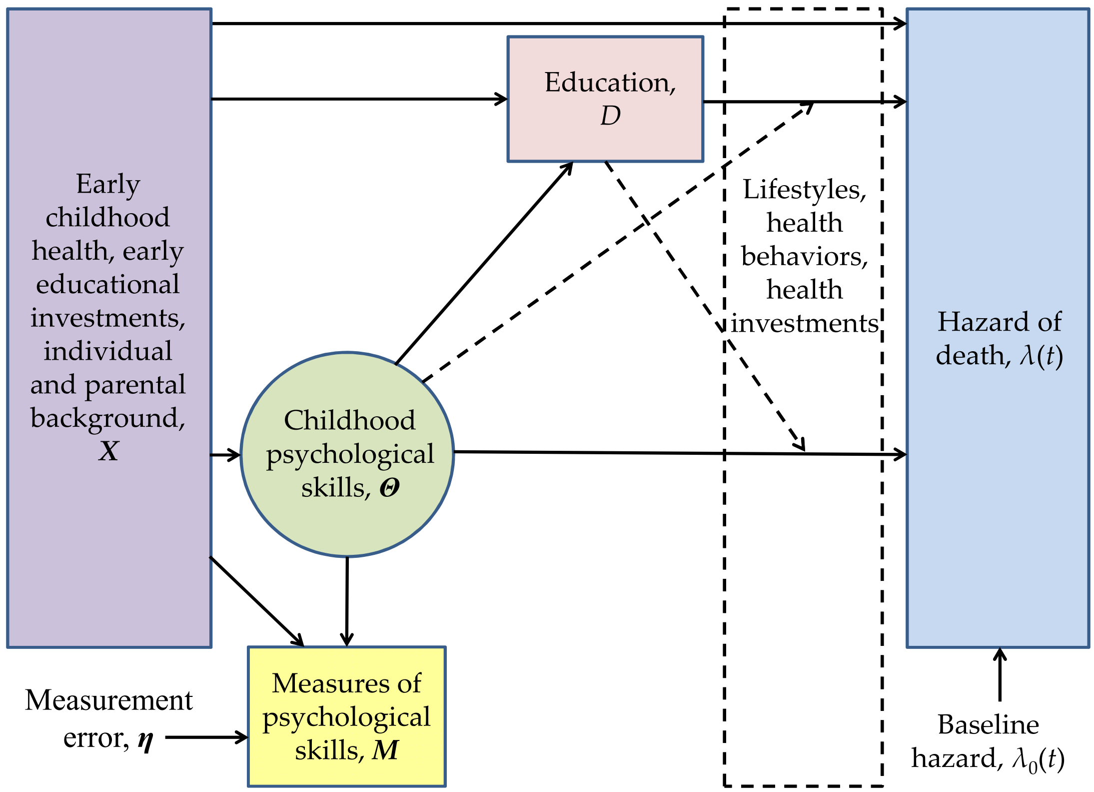
This paper contributes to two distinct literatures: health economics and economics of human development. In the health economics literature, even though education and longevity strongly correlate, the claim of causality is still controversial despite the major importance of this relationship for both public policy and for theories that are foundational of health economics as a discipline (Galama and van Kippersluis, 2013; Grossman, 1972).

It is useful to distinguish two major ranges of formal education that have received unequal attention in the literature: compulsory and post-compulsory education. The effect of compulsory education on longevity has been studied extensively using changes in compulsory schooling laws as natural experiments, but authors disagree on the causal status of education (e.g., Albouy and Lequien, 2009; Clark and Royer, 2013; Lleras-Muney, 2005; Mazumder, 2008; van Kippersluis et al., 2011).[2]

Unlike the effect of compulsory education, the effect of post-compulsory

[1] Kenkel (2000) describes *primary prevention* as a set of actions including lifestyles decisions.
[2] See Web Appendix A for more details about this and other literatures.

Figure 1: Developmental Origins of Longevity



Notes: This scheme is a simplified visualization of the statistical model estimated in this paper. Colored rectangles denote observable variables. The dashed rectangle denotes mediators that are not explicitly modeled in this paper but are modeled in a companion paper (Hong, Savelyev, and Tan, 2014). A circle denotes a vector of latent skills. Solid lines denote causal links; dashed lines denote interactions.

education on longevity is unexplored, perhaps since suitable natural experiments are less readily available. An exception is a recent working paper by Buckles et al. (2013), which uses the avoidance of the Vietnam War draft as a source of identification and finds a strong and statistically significant effect of college graduation on longevity.

My paper further explores the effect of post-compulsory education on longevity, and complements the paper by Buckles et al. in a number of ways. First, I use a methodology of causal effect identification that is an alternative to the use of natural experiments and is based on a combination of advanced econometric techniques controlling for unobserved heterogeneity (Heckman and Singer, 1984; Heckman et al., 2006).

All statistical methods for causal effect identification are based on assumptions and have limitations, even "gold standard" ones, such as randomized controlled experiments (Deaton, 2009; Heckman, Moon, Pinto, Savelyev, and Yavitz, 2010; Heckman and Vytlacil, 2007a), not to mention natural experiments, such as instrumental variable (IV) methods. Limitations of IVs are numerous: IVs are often weak, precision relative to OLS is low, and exogeneity of the IVs is usually a rhetoric-based assumption, which is hard to test directly (e.g., Cameron and Trivedi, 2005). Also, the IV method breaks down when the monotonicity assumption is violated (Heckman and Vytlacil, 2005). Moreover, the effect is only identified for a specific population that is induced to change behavior by the instrument. The OLS, despite its bias, might be closer to the policy-relevant treatment effect than the IV (Carneiro et al., 2011). In particular, the regression discontinuity estimator identifies the causal effect at the point of discontinuity, which is not necessarily the policy-relevant effect (Heckman and Vytlacil, 2007b). Since all statistical methods have their pros and cons, accumulating evidence based on alternative methods is productive, especially given that results based on natural experiments are at odds with each other, as mentioned above.

Second, I study a different population and observe mortality over a much longer age range than Buckles et al.[3] Finally, I show the effects of various levels of post-compulsory education on a number of fundamental longevity-related outcomes. One such outcome is the survival function, a key parameter in the inter-temporal model of educational investment presented in Section

[3] I study white men and women with high intelligence born in 1904–1915 over 70 years of life; Buckles et al. study white men from the general population born in 1942–1953 over the period 1982–2007.

3.1. Other such outcomes include the hazard of death, life expectancy, and the value of statistical life. For comparison with the literature, I construct a measure of mortality that is comparable to the specific aggregated measure of mortality used by Buckles et al. (2013) and obtain similar results.[4]

I also contribute to the emerging literature in economics of human development, in which it is an important part of the agenda to allow for a multi-dimensional vector of correlated personality skills grounded in psychological theory, a task that requires both excellent data and computational intensity (Almlund et al., 2011; Borghans et al., 2008). In this paper I relax the skill orthogonality assumption and account for personality factors that are closely linked to the contemporary and well-established taxonomy of personality, referred to as the Big Five, and find effects of personality on longevity, an unexplored outcome in the literature of economics of human development. Note that the association between certain personality skills and longevity has been established by psychologists based on the same data (Friedman et al., 2010, 1995, 1993). These papers, however, failed to document the exploratory and confirmatory factor analysis of personality measures, did not eliminate the attenuation bias due to measurement error, did not test the proportional hazard assumption behind the Cox model of mortality, and did not attempt to establish causal inference. These papers missed a number of results of this paper such as effects of Extraversion, IQ, and Education on longevity.

I use the Terman data of children with high ability (Terman, 1986), a dataset of about 1,500 subjects from California. The dataset fits well into the study of developmental origins of longevity since it contains a unique combination of measures: IQ, personality, and detailed family background around

[4]Longevity results of this paper and of the paper by Buckles et al. (2013) are in line with a number of papers that identify effects of post-compulsory education on health-related outcomes other than longevity (Conti et al., 2010; Currie and Moretti, 2003; de Walque, 2007; Grimard and Parent, 2007; Heckman et al., 2014). See Web Appendix A for more details.

age 12, followed by 70 years of prospective observations of education, important life events, and mortality. Despite an unusual statistical population, my results contribute substantially to our understanding of the developmental origins of longevity.[5]

Applying a methodology of causal effect identification similar to that used in Heckman et al. (2006), I estimate a system of equations that includes the Cox proportional hazard model of mortality, the generalized ordered logit model of schooling choice, and a system of equations linking a low-dimensional set of latent factors to their multiple noisy measures. On top of controlling for a detailed set of background variables, I also control for ability via IQ and a set of latent personality factors that resemble the Big Five—a set that many psychologists view as comprehensive. I test this model against an alternative that accounts for possible additional unobserved heterogeneity using the latent class technique (Heckman and Singer, 1984) and find no evidence against the null, a result that is in line with a relatively homogenous sample (high IQ white people from California) and a substantial set of observable and latent controls motivated by the literature. The mechanisms behind the treatment effects that we find in companion papers reinforce the causality claims (Hong, Savelyev, and Tan, 2014; Savelyev and Tan, 2014). I acknowledge limitations of this methodology.

Results of this paper differ greatly by gender. For males, I find that Conscientiousness, Extraversion, and IQ strongly decrease mortality, but IQ is only predictive for ages before 50. (The time-dependence of the IQ effect could be an artifact of this particular generation that survived the Great Depression and World War II.) I also find that childhood Conscientiousness interacts with Doctorate degree, so that for future Doctorates, childhood Conscientiousness is no longer beneficial for longevity even though it is highly beneficial for peo-

[5]See a discussion of external validity and data limitations in Section 4.

ple with less-advanced degrees. As a result, the return to a Doctorate degree with respect to longevity declines with the level of childhood Conscientiousness. The treatment effect of a Bachelor's degree on life expectancy at age 30 is 8.6 additional years of life relative to high school education. For a statistical man, the longevity boost induced by a college education is worth as large as $810,000 of 2012 US dollars as a conservative estimate.[6] Finally, while the direct effects of childhood psychological skills on longevity are strong, I do not find any strong and statistically significant indirect effects of psychological skills through education.

Females live even longer than males with advanced degrees, but I do not find any statistically significant effects of education and skills except for a beneficial effect of IQ on mortality below age 50, the same effect that I find for males. Finding an effect of education for males but not for females is in line with Van Den Berg et al. (2012), who have similar findings for compulsory schooling of Danish twins born about 20 years before the Terman cohort. I argue that the lack of effects for females born in the early 20th Century may not apply to contemporary females.

2 Terman Data

The Terman Study started in 1922 and continued through 1991. The sample consists of 856 males and 672 females selected for their high ability based on teachers' nomination followed by an IQ test with a cut-off value of 140. The subjects (who are white and mostly well off[7]) were born, on average, in 1910. The study has an attrition rate below 10%, which is exceptionally low for a

[6] This number does not directly account for any other benefit of college education such as higher wages, greater employment, lower crime, greater investments in children etc.

[7] Terman et al. (1925) refer to the economic status of a majority of families as "fairly comfortable," and indicates that only a few families were "truly in poverty."

70-year-long prospective study. Moreover, the lost subjects are known not to differ systematically in terms of education, income, and demographic factors (Sears, 1984). There is also no evidence that members of the attrited group differ significantly from others on measures of personality (Friedman et al., 1993).

One important benefit of the longitudinal nature of the Terman study, with detailed education data collected multiple times prospectively and retrospectively, is that measurement error in education (e.g., Ashenfelter and Krueger, 1994), is bound to be negligible since our education variable is based on all available life-cycle information.

Background variables in this paper can be grouped into six categories: general intelligence, early health, early childhood investments, parental longevity and background, World War II Experience, and cohort variables. See Table 1 for information about specific variables within these categories.

I restrict the data based on a number of criteria chosen prior to estimation. I exclude subjects who: (1) were not born in the period 1904–1915;[8] (2) are missing both parents' and teachers' personality trait ratings; (3) dropped out from high school;[9] (4) died in service during World War II; (5) had severe diseases such as cancer in their early life; (6) have missing education data; and (7) died or attrited before age 30. The final estimation sample contains 680 males and 529 females. Criteria (1) and (2) are similar or identical to those used by psychologists (Martin et al., 2007).[10]

Measuring Personality Skills Although there are various ways to define personality skills, the Big Five taxonomy of personality is an established and

[8]This restriction makes the cohorts more comparable by excluding a small number of respondents in the tails of the year of birth distribution.

[9]High school dropouts are 16 outliers with a likely case of reverse causality between education and health, which I wish to minimize.

[10]See Web Appendix B for more details on the Terman data.

Table 1: Education and Background Variables

Variable	Year of measure-ment	Males Mean	Males Standard Error	Females Mean	Females Standard Error
Highest Education Level					
High School Graduate	1922-1968	0.101	(0.012)	0.112	(0.014)
Some College	1922-1968	0.165	(0.014)	0.202	(0.017)
Bachelor's Degree	1922-1968	0.300	(0.018)	0.420	(0.021)
Master's Degree or equivalent	1922-1968	0.184	(0.015)	0.216	(0.018)
Doctorate[(a)]	1922-1968	0.250	(0.017)	0.051	(0.010)
General Intelligence					
IQ[(b)]	1922	149.3	(0.405)	148.5	(0.446)
Early Health					
Normal birth or no birth problems mentioned[(c)]	1922	0.571	(0.019)	0.629	(0.021)
No breastfeeding[(c)]	1922	0.091	(0.011)	0.085	(0.012)
Health rating in 1922[(d)]	1922	8.526	(0.075)	9.027	(0.083)
Physical energy rating in 1922[(d)]	1922	8.219	(0.073)	8.834	(0.078)
Mother's poor health during pregnancy[(c,e)]	1922	0.173	(0.015)	0.178	(0.017)
Low birthweight (below 2.5 kg)[(c,e)]	1922	0.019	(0.005)	0.047	(0.010)
Persistent mouth breathing in 1922[(e)]	1922	0.024	(0.006)	0.020	(0.007)
Frequent or very frequent colds in 1922[(e)]	1922	0.166	(0.015)	0.112	(0.014)
Headaches mentioned in 1922[(e)]	1922	0.170	(0.015)	0.181	(0.018)
Headaches frequent or severe in 1922[(e)]	1922	0.006	(0.003)	0.010	(0.005)
Nutrition poor or fair in 1922[(e)]	1922	0.092	(0.012)	0.071	(0.012)
Early Educational Investments					
Logarithm of the amount of parental tutoring, ages 2-7[(f)]	1922	0.450	(0.014)	0.409	(0.016)
Logarithm of the duration of private tutoring, ages 2-7[(f)]	1922, 28	0.105	(0.014)	0.344	(0.026)
Parental Longevity and Background					
Mother is deceased by 1922	1922	0.028	(0.006)	0.032	(0.008)
Father is deceased by 1922	1922	0.081	(0.010)	0.074	(0.011)
Parents are divorced before 1922	1922	0.050	(0.008)	0.047	(0.009)
Father has at least a bachelor's degree	1922	0.291	(0.017)	0.253	(0.019)
Mother is employed	1922	0.126	(0.013)	0.132	(0.015)
Father is a professional	1922	0.243	(0.016)	0.276	(0.019)
Either parent from outside the US	1922	0.304	(0.018)	0.267	(0.019)
Either parent from Europe	1922	0.218	(0.016)	0.202	(0.017)
Parental finances adequate	1922	0.371	(0.019)	0.384	(0.021)
Parental social position below average	1922	0.253	(0.017)	0.153	(0.016)
World War II Experience					
WWII Participation	1945	0.410	(0.019)	0.026	(0.007)
WWII Combat Experience	1945	0.093	(0.011)	0.004	(0.003)
Cohort					
Cohort: 1904 - 1907	1922	0.237	(0.016)	0.172	(0.016)
Cohort: 1908 - 1911	1922	0.468	(0.019)	0.467	(0.022)
Cohort: 1912 - 1915	1922	0.296	(0.018)	0.361	(0.021)
Age in 1922		11.84	(0.112)	11.30	(0.121)
Estimation Sample		680		529	

Notes: [(a)]Includes both entry-level and research-level doctoral degrees such as M.D., LL.B., LL.M, and Ph.D.[(b)]The best estimate of IQ in 1922 is provided by survey organizers and is based on all available test scores including Stanford Binet and Terman Group Tests. [(c)]Indicators of conditions at birth and early health investments (breastfeeding) are reported retrospectively by parents in 1922. [(d)]An average over non-missing values of teachers' and parents' ratings is used (rating can range from 1 to 13). [(e)]Variables marked with "(e)" are not controlled for in the final model, but robustness checks show that controlling for them does not change model results in any significant way, while reducing the estimation sample size. [(f)]Duration of parental tutoring (in hours/week) and private tutoring (in weeks, where 1 week is 168 hours of tutoring) are transformed using the natural logarithm, ln(1+duration).

widely-used way to do so (John and Srivastava, 1999). The data on personality collected in 1922 and 1940 by Terman and coworkers are theoretically and empirically close to the Big Five taxonomy (Martin and Friedman, 2000). Definitions of the Big Five skills are provided by John and Srivastava (1999). In short, conscientious people are planful, goal-directed, and follow rules; open people enjoy new experiences and ideas; extraverted people like socializing; agreeable people are nice to others; and neurotic people are emotionally unstable.[11] In this paper, following standard psychometric techniques, I represent latent personality skills using factor analysis documented in detail in Web Appendix C.

3 Methodology

3.1 Conceptual Framework

Consider a generalization of a discrete time intertemporal economic model (Becker, 2007) in order to demonstrate the economic role of both education and psychological skills in extending life.[12] I incorporate psychological skills into the model as exogenous parameters: individuals cannot choose their levels of psychological skills, but skills can possibly be influenced by the environment, which includes parents, peers, and educators.[13]

Consider a two-period model, which demonstrates the main features of the economic problem and is easily generalizable to a multiple-period case.[14]

[11] See Web Appendix C for more details. In particular, Table C-13 shows measures that define factors in this paper.

[12] Assumptions of the motivating conceptual framework do not necessarily affect the validity of statistical results.

[13] In this simple model, I abstract from a possibility proposed by Becker and Mulligan (1997) that individuals may rationally invest in their imagination capital with the aim of reducing the discount on future utilities.

[14] Since I do not calibrate the economic model, generalizing it for more than two periods in this paper would complicate model presentation without providing any benefit such as

Let capital and annuity markets be perfect and earnings not be taxed. An individual maximizes the expected utility with respect to consumption $\{C_1, C_2\}$ and education D:

$$u_1(C_1) + B(\boldsymbol{\Theta}) \cdot S(\boldsymbol{\Theta}, D) \cdot u_2(C_2), \tag{1}$$

where B is the discount factor, S is the survival probability, u_t is the utility function at period of life t. Let the discount factor B and survival S depend on psychological skills $\boldsymbol{\Theta}$.[15] Let S also depend on education D.[16] Assumption $S = S(\boldsymbol{\Theta}, D)$ is theoretically justified by a companion paper by Savelyev and Tan (2014), who show the role of health-related consumption and health investments as mediators of the effect of psychological skills and education on health stock and longevity.

The maximization is subject to the intertemporal budget constraint

$$C_1 + g(\boldsymbol{\Theta}, D) + \frac{S(\boldsymbol{\Theta}, D)}{(1+r)} C_2 = A + Y_1(\boldsymbol{\Theta}) + \frac{S(\boldsymbol{\Theta}, D)}{(1+r)} Y_2(\boldsymbol{\Theta}, D), \tag{2}$$

where Y_1 and Y_2 are earnings in period 1 and 2, and g is the cost of education investment.[17] Earnings Y_2 in the second period and cost of education g depend on years of education D and psychological skills $\boldsymbol{\Theta}$.

It is straightforward to show from the first order conditions that marginal benefits of education include the longevity benefit, $B(\boldsymbol{\Theta}) \frac{\partial S(\boldsymbol{\Theta}, D)}{\partial D} u_2(C_2)$, representing greater expected utility due to higher probability to survive to the

better fit to the data.

[15]See Almlund et al. (2010) for a discussion of the relationship between psychological skills and time preference.

[16]In the theoretical part, I treat D as continuous. The model can be reformulated to use categorical highest degree completed as in the rest of the paper at the expense of losing concise mathematical representation of results.

[17]From theoretical considerations and in line with the psychological literature, we can expect the cost of education to decrease with Cognition, Conscientiousness, and Openness, skills that make learning more effective. We also can expect Extraversion to have the opposite effect since studying implies forgone socializing, which is of higher value for those who are more extraverted.

second period, induced by additional education. The benefit is amplified by discount factor B and utility $u_2(C_2)$, which makes the benefit higher for patient people (who have high B), and for wealthy people (who can afford high C_2). Both discount factor and earnings can be influenced by investments in childhood personality skills, thus adding to incentivizing the education investment through greater marginal longevity benefit.

I supplement the theory with a number of empirical results. I confirm the assumption of the model that $S = S(D, \boldsymbol{\Theta})$. I also empirically find: (1) $\frac{\partial S}{\partial \Theta^C} > 0$, $\frac{\partial S}{\partial \Theta^E} > 0$, $\frac{\partial S}{\partial \Theta^G} > 0$ (higher childhood Conscientiousness, Extraversion, and IQ lead to higher survival); (2) $\partial D/\partial \Theta^C > 0$ and $\partial D/\partial \Theta^G > 0$ (higher childhood Conscientiousness and IQ increase education); (3) At the highest education level $\frac{\partial^2 S_t}{\partial D \partial \Theta^C} < 0$ (Conscientiousness and Doctoral education are substitutes). (4) $\frac{\partial S_t}{\partial D} > 0$ (college education increases longevity). I also find relationships similar to the ones I found for S for other outcomes representing longevity.

3.2 Statistical Models

From this section on, let D be a categorical choice of the highest education level obtained in life. For highly intelligent Terman subjects, D takes values from 1 to 5: (1) high school graduate, (2) some college education, (3) Bachelor's degree, (4) Master's degree, and (5) Doctorate.

Main Model The gold standard for modeling the hazard of death is the semi-parametric Cox proportional hazard (PH) model (Cox, 1972). I use a generalization of the Cox model that allows regression coefficients to vary over time (Asparouhov et al., 2006).

My most preferred Cox model specification justified in Web Appendix D can be written as

$$\lambda(t|\boldsymbol{\Theta}, D, \boldsymbol{X}) = \begin{cases} \lambda_{01}(t) \cdot \exp(\beta_1^G \Theta^G + Z(\boldsymbol{\Theta}, D, \boldsymbol{X})), & \text{for } 30 < t \leq 50 \\ \lambda_{02}(t) \cdot \exp(\beta_2^G \Theta^G + Z(\boldsymbol{\Theta}, D, \boldsymbol{X})), & \text{for } 50 < t \leq 86, \end{cases} \tag{3}$$

where λ is a hazard of death, λ_0 is a nonparametric baseline hazard, Z is defined as

$$Z(\boldsymbol{\Theta}, D, \boldsymbol{X}) = \sum_{d=1}^{5} \alpha_d 1[D = d] + \sum_{i \in \mathcal{I}} \beta^i \Theta^i + \gamma \Theta^C 1[D = 5] + \boldsymbol{\delta X},$$

i is an index for personality skills, and $1[D = d]$ is an indicator that education D has realization d. In this formula, α_3 and α_4 are both set to zero as effects of reference education levels;[18] $\mathcal{I} = \{C, O, E\}$, which stands for Conscientiousness (C), Openness (O), and Extraversion (E). The third term on the right-hand side represents an interaction between Conscientiousness Θ^C and education at the doctorate level ($D = 5$).

I test this model against an alternative that accounts for possible additional unobserved heterogeneity using the latent class technique (Heckman and Singer, 1984) and find no evidence against the null.[19]

I use a generalized ordered logit model (e.g., Williams, 2006) for studying schooling choice. The choice of this standard model is justified in Web Appendix D.

In order to account for latent personality variables as determinants of longevity and schooling choice, I estimate a factor model (4) called "measurement system" simultaneously with the Cox model and the schooling model using the maximum likelihood estimator and the expectation-maximization algorithm. Identification of such models is standard and discussed in a num-

[18]Reference education level in the Cox model is Bachelor's and Master's education combined. I find no difference in longevity between people with Bachelor's and Master's degrees.

[19]See Web Appendix E for latent class analysis.

ber of papers such as classic Anderson and Rubin (1956), and more recent Heckman, Pinto, and Savelyev (2013), Heckman et al. (2014), and Williams (2011). The model can be written as

$$\boldsymbol{M} = \boldsymbol{\xi} + \boldsymbol{\psi}\boldsymbol{\Theta} + \boldsymbol{\pi} A + \boldsymbol{\gamma}\boldsymbol{X} + \boldsymbol{\eta}, \tag{4}$$

where $\boldsymbol{M}$ is a vector of K personality measures that proxy latent factors $\boldsymbol{\Theta}$;[20] $\boldsymbol{\xi}$ is a vector of intercepts; $\boldsymbol{\psi}$ is a $K \times I$ matrix of factor loadings, which represents relationships between correlated latent factors $\boldsymbol{\Theta}$ and personality measures; $\boldsymbol{\pi}$ is a vector capturing the relationship between the age of testing A and personality measures;[21] $\boldsymbol{\gamma}$ is a $K \times Q$ matrix that relates a vector of background control variables $\boldsymbol{X}$ to measures; $\boldsymbol{\eta}$ is a vector of measurement errors.[22]

A Model Allowing for a Comparison with the Literature In order to obtain estimates of the effect of schooling on mortality that are based on the methodology of this paper but are comparable with those by Buckles et al. (2013), I also estimate a linear model controlling for latent factors, IQ, and background variables. I define $MR(y_1, y_2)$ as a binary variable that takes value one if person died during years from y_1 to y_2 and value zero if person survived through the period. Let CE be a binary variable denoting that the highest education level in life is Bachelor's degree or above. I estimate the

[20] See Web Appendix C for a justification of the measurement system specification.

[21] I find a strong and statistically significant effect of age A on measures of Conscientiousness and Extraversion, implying that it is necessary to age-adjust measures of personality in the Terman data. The effect of age on measures of Conscientiousness is uniformly positive, while it is mixed on measures of Extraversion. I find no age effect on measures of Openness.

[22] See Web Appendix D for further details on the factor model.

following linear model

$$MR(y_1, y_2) = q_0 + q_1 CE + \sum_{i \in \mathcal{I}} q_2^i \boldsymbol{\Theta}^i + q_3 \Theta^G + \boldsymbol{q}_4 \boldsymbol{X} + \epsilon. \tag{5}$$

for various years y_1 and y_2 simultaneously with the measurement system (4).

3.3 Treatment Effect Identification and Calculation

The Effect of Education There are two major statistical problems that prevent us from interpreting the correlation between education and longevity as a causal effect (e.g., Grossman, 2000): (1) confounding factors such as ability that affect both education and longevity, and (2) reverse causality (expected longevity affects education choice). I address both problems in order to separate out the causal effect of education on longevity.

I employ a method of causal effect identification that relies on the extraordinary richness of Terman data and a possibility to control for unobserved heterogeneity through modeling both latent personality skills (Heckman et al., 2006) and latent classes of individuals (Heckman and Singer, 1984). I assume that conditional on detailed background characteristics and latent classes, all dependence across education and potential longevity outcomes comes from cognitive and personality skills. This identification strategy, which is similar to the one used in Heckman et al. (2006), should eliminate the omitted variable bias under the assumptions of the model. Note that the Big Five taxonomy captures both Victor Fuchs's favorite candidates for confounders of the relationship between education and health: time preference and self-efficacy (Fuchs, 1982, 1997). Time preference is related to Conscientiousness, while self-efficacy, which is the belief that one is able to exercise control over one's own environment and achieve one's goals, is related to Neuroticism (see Almlund et al. (2011) for a survey).

To address the reverse causality problem, I control for various early health conditions and other background characteristics that subjects may use to anticipate a short life, thus resulting in low educational investments. First, I drop a few subjects from the sample who had severe medical conditions such as cancer early in their life and so could expect early death.[23] Second, I control for longevity predictors such as early childhood health, childhood health in 1922, early parental death, early educational investments, parental social status, and parental wealth, among other controls. Finally, I restrict consideration to subjects who survived through age 30, which both rules out people who died early and makes education choice a past event by construction.[24]

It would be valuable to compare methodology used in this paper with alternative ones based on the same data, but I was not able to find any reliable instrumental variable for education as a cause of longevity.[25]

Even though it is generally impossible to fully account for confounding factors and reverse causality, the method described above uses all available means to minimize biases and, hopefully, makes them negligible.

The Effect of Psychological Skills While the biological view of psychology still contends that developments of personality in adulthood are biologically predetermined (e.g., McCrae et al., 2000), this traditional view of personality

[23]Controlling for them using a dummy variable is not practical when bootstrap-based inference is used since there are only a few such severe cases in the sample, which would create the collinearity problem in some pseudo-samples. Longevity of children with severe diseases should be studied based on specific data of such children.

[24]Some of those who died early could anticipate their death with consequences for education. Education is largely a past choice after 30 since only 2.3% of respondents were still students at that age (see Figure M-1 of the Web Appendix).

[25]I considered using the Great Depression, World War II, and other variables as instruments for schooling. I do not document the results here, since, even though I obtain a positive IV estimate of the effect of education on longevity that is statistically significant at 10% level, monotonicity of the instruments is questionable, the instruments are not strong enough (Stock et al., 2002), and standard errors are too large for the estimate to be informative. Had I considered instruments as the only possible treatment effect identification tool, the rich and unique Terman data would be useless.

as stable and non-malleable has been challenged by recent literature. Roberts and Bogg (2004) provide evidence that Conscientiousness and socioenvironmental factors influence each other. Heckman, Pinto, and Savelyev (2013) show experimental evidence that skills closely related to Conscientiousness can be improved through educational intervention in early life with major consequences for later life outcomes. Papers by Almlund et al. (2011) and Conti and Heckman (2014) survey a large body of literature and support the view that personality skills are malleable and can be affected by interventions.

As in the case with the education effect identification, there might be confounding factors, such as parental skills, that affect both childhood skills (e.g., through investments) and longevity (e.g., through providing a personal example of healthy lifestyles). Poor early health may affect both childhood skills and mortality in adulthood. Reverse causality is also not impossible, since anticipation of shorter lifespan may affect investments into childhood skills. To minimize a possible omitted variable bias, I control for a detailed set of individual and family background variables, $\boldsymbol{X}$, thus eliminating $\boldsymbol{X}$ and variables that are closely related to $\boldsymbol{X}$ as confounding factors. Even though I do not observe parental personality, I do observe education and occupation of both mother and father, as well as their wealth and social standing. I expect these multiple controls to indirectly capture the most of productive and health-relevant parental skills and lifestyles.[26] Early health measures, the childhood health measure, and other controls should minimize the bias due to reverse causality. As above, evidence from latent class analysis can be interpreted as an indication of no sizable unobserved heterogeneity.

[26]For instance, parental education and skill level of occupation is expected to positively correlate with parental Conscientiousness and IQ. Higher level of earnings likely correlates with healthy lifestyles and Extraversion.

Understanding Mechanisms Reinforces the Causality Claim The influential Surgeon General's Report (Terry et al., 1964) was highly convincing of the causal effect of tobacco smoking on mortality despite relying on correlational evidence since strong correlational evidence was combined with evidence of concrete chemical and biological mechanisms of smoking causing cancer. Likewise, results of our companion papers (Hong, Savelyev, and Tan, 2014; Savelyev and Tan, 2014) reinforce treatment effect evidence from this paper with evidence on mechanisms. As described in Web Appendix A, our papers show multiple channels through which education and personality may affect longevity: weight control, smoking tobacco, heavy drinking of alcohol, physical exercise, earnings, social ties, and stable marriage.

Outcomes of Interest I estimate treatment effects on the following four outcomes describing longevity: the hazard of death, survival function, life expectancy, and an aggregated measure of mortality similar to that used in Buckles et al. (2013). I also evaluate the effects on longevity in US dollars.

Estimation of survival function S involves many technicalities that are described in Web Appendix F. I estimate S as a function of age t, starting age t_0 at which a person is known to be alive, personality $\boldsymbol{\theta}$, and education d.[27] Once we know S, we can calculate life expectancy at age t_0 for any $t_0 \geq 30$:

$$e(t_0, \boldsymbol{\theta}, d) = \int_{t_0}^{\infty} S(t, t_0, \boldsymbol{\theta}, d)\, dt. \tag{6}$$

In order to evaluate the effect of education on survival in US dollars, I calculate the value of remaining life V_R at age t_0 using the methodology from

[27] Realizations $\boldsymbol{\theta}$ and d correspond to random variables $\boldsymbol{\Theta}$ and D.

Murphy and Topel (2006). Generally, V_R can be written as:

$$V_R(t_0, d) = \int_{t_0}^{\infty} v(t, d) S(t, t_0, d) e^{-r(t-t_0)}\, dt, \tag{7}$$

where $v(t, d)$ is the value of a life-year at age t for a person with education level d. The effect of education level on V_R, $\Delta V_R = V_R(t_0, d_2) - V_R(t_0, d_1)$, can be decomposed into three terms:

$$\Delta V_R = \underbrace{\int_{t_0}^{\infty} v \Delta S e^{-r(t-t_0)}\, dt}_{\text{value of greater longevity}} + \underbrace{\int_{t_0}^{\infty} \Delta v S e^{-r(t-t_0)}\, dt}_{\text{value of greater quality of life}} + \underbrace{\int_{t_0}^{\infty} \Delta v \Delta S e^{-r(t-t_0)}\, dt}_{\text{interaction term}}. \tag{8}$$

One of the aims of this project is to evaluate the monetary value of the longevity contribution, the first term of this decomposition.

I use the shape of the $v(t)$ function from Murphy and Topel (2006) and follow the authors in using interest rate r of 3.5%. In order to evaluate effects on longevity in today's prices, I multiply $v(t)$ from Murphy and Topel by an adjusting coefficient to achieve the statistical value of life in the Terman population of $9.1 mln US dollars, an estimate that was recently adopted by the US Department of Transportation[28] and is grounded in the most recent economic research (Viscusi, 2013).[29] I use the value of statistical life V_S as defined in Murphy and Topel (2006), a survival-adjusted average of the value of remaining life over a period of economically active life.[30] Given that white

[28]Polly Trottenberg and Robert S. Rivkin. "Guidance on Treatment of the Economic Value of a Statistical Life in U.S. Department of Transportation Analyses," Office of the Secretary of Transportation, U.S. Department of Transportation, 2013. Available at http://www.dot.gov/office-policy/transportation-policy/guidance-treatment-economic-value-statistical-life.

[29]The median estimate based on the literature that used the most reliable data, the Census of Fatal Occupational Injuries, is $9.3 mln (Viscusi, 2013). The US Department of Transportation adopted $9.1 mln based on the same data. Readers who prefer a different estimate of the value of life can easily adjust all estimates in this paper by multiplying them by a ratio of their favorite value of life estimate to $9.1 mln.

[30]See Web Appendix F for more details.

men with high IQ have much higher earnings than a random person from the general population, and that the elasticity of the value of life with respect to earnings is at least 1.0 (Viscusi, 2013), the value of life estimates provided here are conservative. The interpretation of this evaluation is the lower bound of the value of educational investments for the contemporary statistical person from the relevant population if we expect the effects of the investment to be the same as for the Terman cohort.

Average Treatment Effects Consider the average effect of increasing education level from d_1 to d_2 on Y, where Y denotes any outcome of interests such as S, e, V_R or V_S. Based on identification assumptions discussed above in this section, estimated model coefficients for education and skills represent average treatment effects, and so we can write: $\Delta Y(\boldsymbol{\theta}, d_1, d_2) = Y(\boldsymbol{\theta}, d_2) - Y(\boldsymbol{\theta}, d_1)$ and, after integrating skills out, $\Delta Y(d_1, d_2) = Y(d_2) - Y(d_1)$. The average treatment effects of skills given education (the direct effect of skills) is defined by $\frac{\partial Y(\boldsymbol{\theta},d)}{\partial \theta^i}$, for $i \in \{C, O, E, G\}$.

For comparison with Buckles et al. (2013) I use an estimate $\hat{q}_1$ from equation (4) multiplied by 1000. The interpretation of $1000\hat{q}_1$ given the assumptions of the statistical model is the causal effect of college education on the number of deaths among 1000 of a population between years y_1 and y_2.

4 Empirical Results and Discussion

I first motivate the empirical study based on descriptive statistics. Then, I discuss estimates of the main model and proceed with the analysis of treatment effects on survival, life expectancy, and an aggregate measure of mortality that was used by Buckles et al. (2013). Finally, I discuss a number of robustness checks.

Descriptive Results Consider first dependencies among variables without imposing any parametric assumptions. Figure 2 shows the Kaplan-Meier estimates of survival by education and gender. For males, higher levels of education correspond to higher survival. Indeed, while only 23% of high school graduates survive to age 80, 60% of doctorates do.[31] For females, we can see no difference between the survival curves from high school to Master levels. Although the estimated survival curve for the sample of 27 females with doctoral degrees stays below other survival curves, confidence intervals for the survival curve of female Doctorates are too large to claim that the curve differs from others.[32] Other documented nonparametric results include associations between longevity and skills of Conscientiousness and Extraversion, as well as the association between skills and education outcomes.[33]

Treatment Effects of Education and Psychological Skills on the Hazard of Death Figure 3 shows multiplicative effects on the hazard of death λ that include: (1) effects of education levels relative to Bachelor's and Master's levels combined,[34] and (2) effects of early psychological skills conditional on the future choice of education, which are the direct effects of skills as opposed

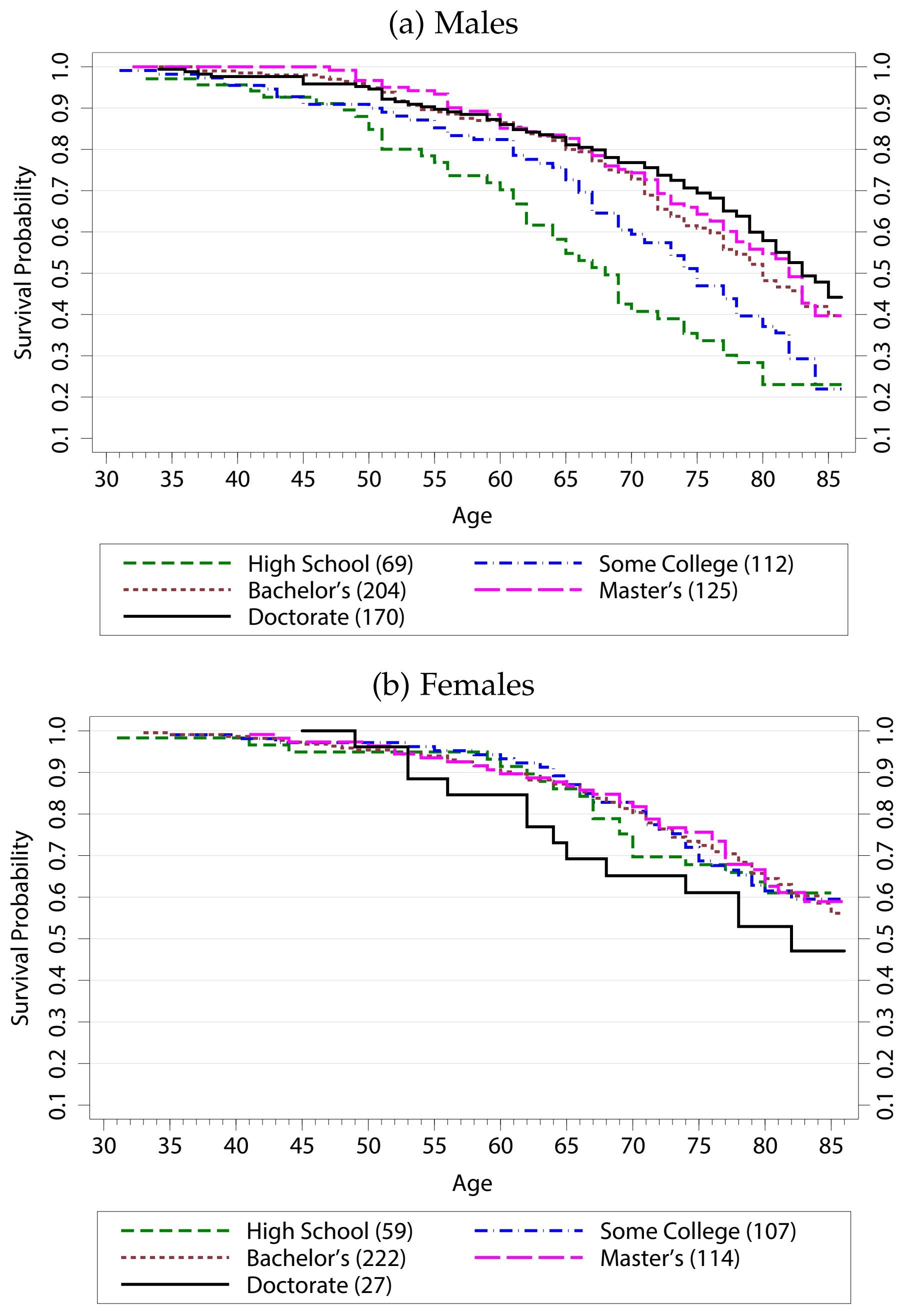
[31]It may seem surprising that 10-11% of high-ability people did not proceed beyond high school. In Web Appendix B I argue that high-school education was perceived as relatively high level of education for this cohort corresponding rank-wise to today's Bachelor's degree.

[32]See Figure M-2 in the Web Appendix, which shows that we can statistically distinguish survival curves for males but not for females. We may also expect that females who chose a male-like degree of that time (a Doctorate) could be more inclined to also have more male-like habits such as smoking and hence die from associated diseases early on. This hypothesis is not supported by the data on the causes of death reported by relatives; but, given low sample size of female doctorates and possible measurement error in the reported causes of death, it is hard to be sure about any statistical inference. In addition, in Web Appendix G, I show that having a doctoral degree for high-ability females born in the beginning of the 20th Century is associated with lower family life satisfaction, lower general happiness, and fewer children. Some of these factors could be behind this unusual pattern of longevity unless the pattern is just an artifact of the data.

[33]To save space, these graphs are shown and discussed in Web Appendix M (see Figures M-3–M-6 for survival curves by personality skills, Figures M-7–M-8 for kernel densities of psychological skills by education, and Figure M-9 for personality skills by gender).

[34]There is no difference in longevity between Bachelor's and Master's levels.

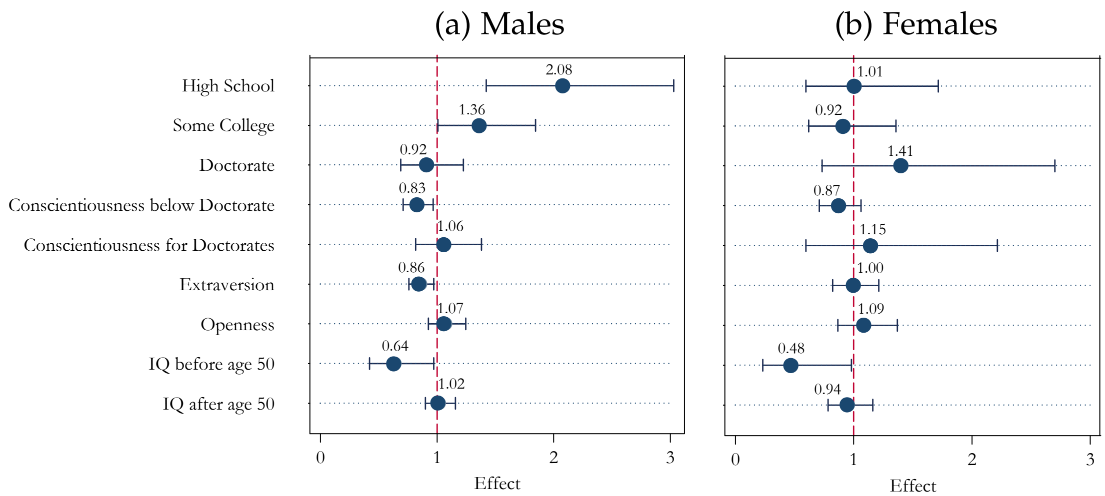
Figure 2: Kaplan-Meier Survival Function by Education



Notes: Probability of survival is conditional on survival to age 30. Sample sizes are shown in parentheses. Education groups are mutually exclusive and refer to the highest level of education obtained in life. Calculations are based on the Terman data. See Figure M-2 of the Web Appendix for pairwise comparisons of curves with confidence intervals shown.

to indirect effects that work through education.[35]

Figure 3: Multiplicative Effects of Education and Psychological Skills on the Hazard of Death



Notes: Effects of education are relative to the baseline Bachelor's or Master's degree. Effects of childhood psychological skills are direct effects conditional on the future choice of education. Bars represent 95% confidence intervals. Corresponding Cox model parameters are presented in Panel 1a of Table 3.

For males, high school graduates have about 100% higher hazard of death than those with a Bachelor's or Master's degree (see Panel (a)). Those with some college education have about 40% higher hazard of death. A Doctorate degree makes no statistically significant difference relative to Bachelor's and Master's degrees.

Further, a one standard deviation increase in childhood Conscientiousness (for men with education below Doctorate) or Extraversion (for men with any level of education) decreases the hazard of death by about 17 and 14% respectively. Finally, IQ decreases the hazard of death by 36% despite already high IQ level in the sample, but only at ages 30–50. As we can see from panel (b), the only statistically significant result for females is a similar effect of

[35]Estimates of the indirect effects are small and statistically insignificant.

IQ. The estimate of the effect of Conscientiousness is similar for males and females, but we cannot distinguish the effect for females from zero due to higher standard error.

These gender differences are consistent with results by Conti and Heckman (2010), who show that both education and personality skills affect health and health behaviors more for males than for females even for the contemporary population. For the Terman population, for which women faced stronger pressure from the society in terms of following certain healthy lifestyles, we should expect even smaller role of skills and education.[36]

Results for Conscientiousness and Education are not surprising given the prior evidence mentioned in the introduction. Results for Extraversion and IQ are novel for a high-ability population. Our companion paper (Savelyev and Tan, 2014) based on the same data suggests that even though Extraversion increases heavy drinking, it also increases earnings and improves mental and general health, which sheds light on some mechanisms of the effect.

At the same time, the unexpected age-dependence of the IQ effect is challenging to interpret. Given that we observe the effect for both males and females, it is unlikely to be just an artifact of the data. There is evidence that the effect is not due to violent deaths such as accidents or suicide.[37] One possible interpretation is that the IQ result is specific to the sample of people born in 1904–1915, who in young adulthood were subject to both physical and psychological challenges associated with the Great Depression and World War II. Higher IQ could provide a survival advantage for dealing with these challenges. Whatever the interpretation of the effect and whatever its generalizability to different cohorts and different populations, it is useful to control for this time dependence in this particular estimation for the sake of better

[36]See also Friedman et al. (1993) for a discussion of these mechanisms.

[37]See Tables M-1 and M-2 and their discussion in Web Appendix M for more details.

model specification. The role of the IQ effect in early life is minor in forming life expectancy since deaths are not frequent at ages 30–50.[38]

Early psychological skills also affect education. As documented in the Web Appendix, education is boosted by Conscientiousness and IQ, but effects are not strong.[39]

Treatment Effect of Education on Survival Function Since I find no education and personality gradient for females in either descriptive nonparametric or most preferred semi-parametric models, all discussion below is for males, for whom the gradient is substantial.

Survival function S is fundamental for making intertemporal economic decisions such as investments in education. S acts as a discount factor for both expected utility and the budget constraint (see Equations (1) and (2)). The importance of S motivates studying its major determinants.

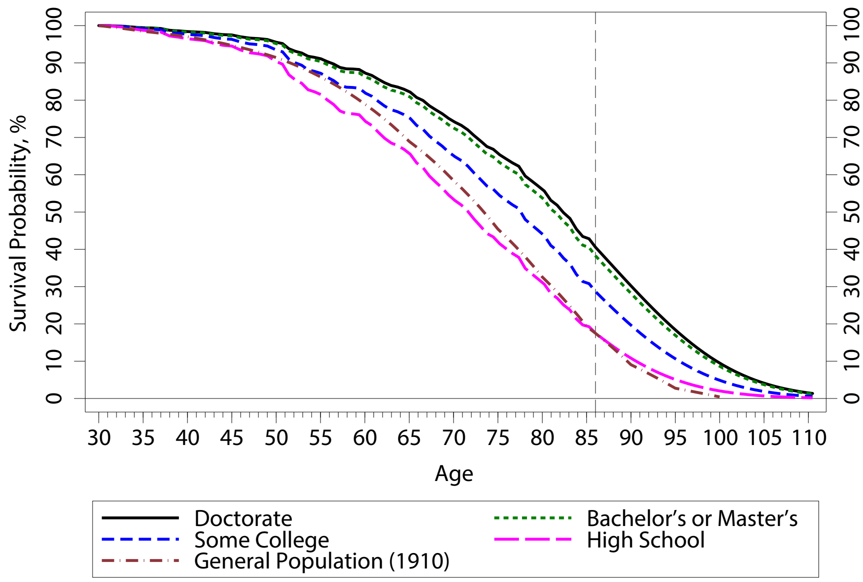
I find that survival monotonically increases with education (see Figure 4).[40] The survival curve for the general population of white males born in 1910 based on the Census data shown in the same figure is most similar with the survival curve for Terman participants who stopped their education at the high-school level. Vertical distances between survival curves by education represent the treatment effect of education on survival. These effects are documented and discussed in the Web Appendix I, with the conclusion that the maximal survival effect of university degrees relative to high school education is archived at age 80 and constitutes statistically significant 22–25 percentage points.

[38]See Figure M-10 of the Web Appendix M illustrating the relatively minor role of IQ in overall survival (panel (a)), but strong role of IQ at ages 30–50 (panel (b)).

[39]See Figures M-11 and M-12, Table M-3, as well as their description in Web Appendix M.

[40]See Web Appendix H for interpolation and extrapolation of the baseline survival function, which is an intermediary step for predicting survival curves. I also discuss the robustness of the survival curve to alternative methods of extrapolation in the appendix.

Figure 4: Model Prediction of the Survival Function by Education, Males



Notes: The vertical dashed line denotes age 86, after which I extrapolate the baseline survival function using the Gompertz-Makeham approach (see Web Appendix H). See Figure M-13 of the Web Appendix for confidence intervals for the survival curves. I calculate the general population survival curve using the Census data on mortality of the 1909–1911 cohort of white males over 100 years of observations (Arias, 2012).

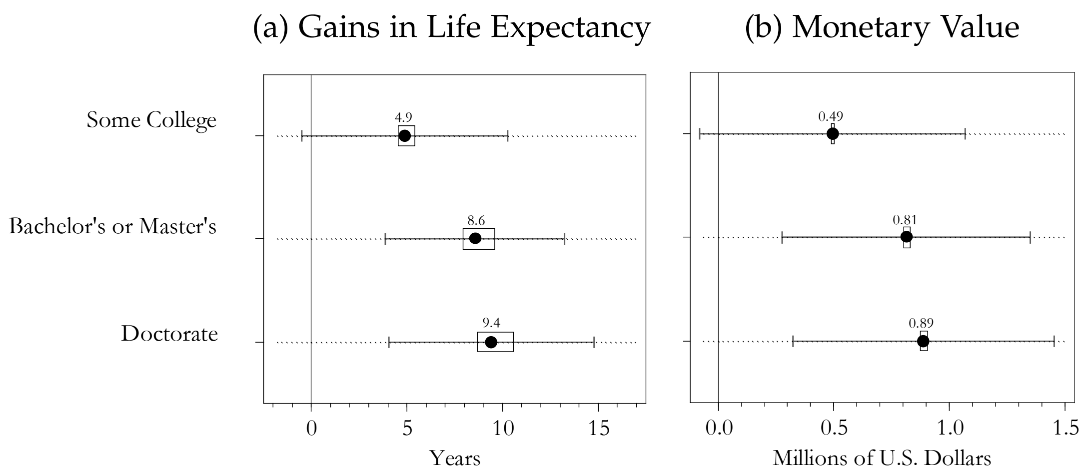
Treatment effects of education on life expectancy, another fundamental characteristic of longevity, are presented in panel (a) of Figure 5. According to the figure, a Bachelor's degree brings 8.6 additional years of life, which is on average 2.15 additional years of life per year of completed 4-year college degree, a remarkably high benefit. According to panel (b), this longevity benefit is evaluated for a statistical person as at least $810,000 per 4 years of college which is $202,500 per year in college.[41] Even though this high longevity gain does not directly include the gains in expected earnings and related benefits, it still justifies the economic cost of studying even at an expensive college.[42]

[41] The evaluation is built on the analysis of the value of remaining life presented in Web Appendix I. See also Figure M-14 of the Web Appendix.

[42] As a conservative back-of-the-envelop calculation, the yearly direct cost of attending a

Finally, rectangles on the graphs representing robustness of estimates to alternative extrapolation methods suggest that extrapolation methodology makes little difference.

Figure 5: Effects of Education on the Life Expectancy and the Corresponding Monetary Value for a Statistical Person, Males

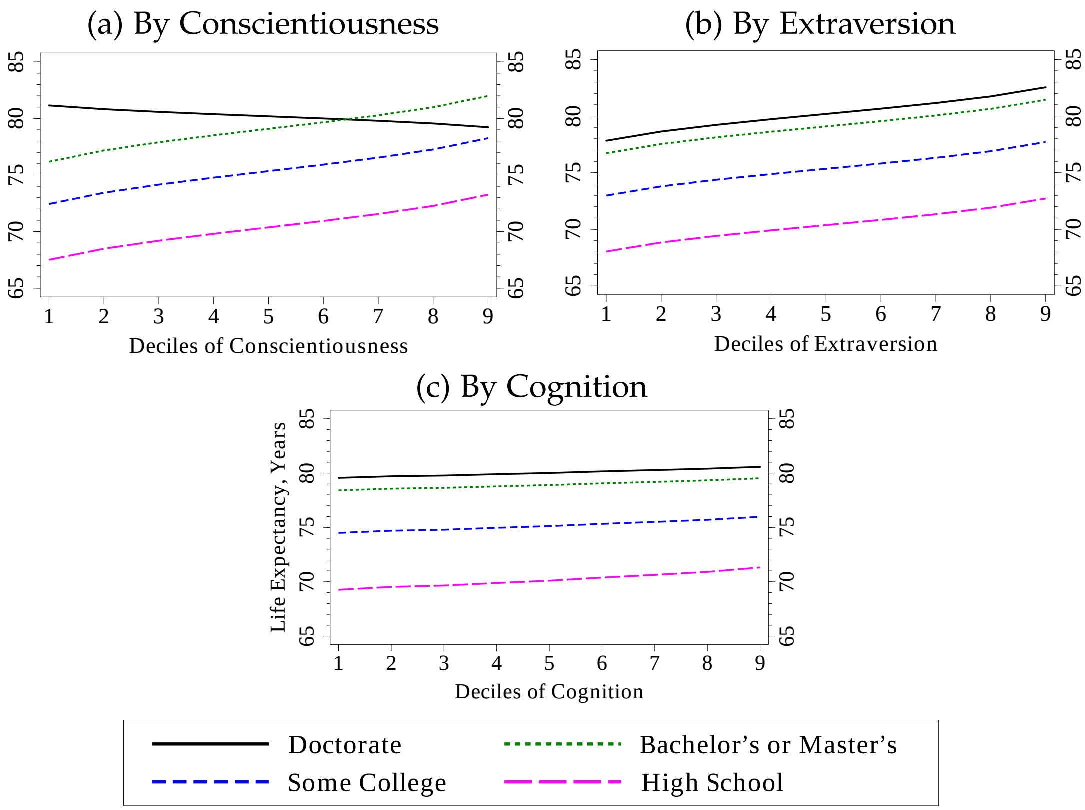


Notes: Effects are relative to the baseline remaining life expectancy at age 30 for high-school graduates, which is 40.7 years (see Figure M-16 of the Web Appendix for life expectancy by education). Black dots represent estimates. Bars represent the 95% bootstrap confidence intervals. Widths of rectangles around dots represent robustness of the estimates with respect to alternative extrapolations of the baseline survival function from age 86 to age 110 documented in Web Appendix H. Monetary values are in 2013 US dollars. Calculations are based on the Terman data.

Effects of Skills on Life Expectancy Conditional on Education Choice Figure 6 shows how life expectancy at birth conditional on survival to age 30 changes depending on deciles of a particular skill, keeping all other skills at

top private college in the US today is about $47,000 (tuition, books and supplies, other fees). The forgone labor income is about $40,000, so that the total economic cost of one year of high-quality education is about $87,000. The value of additional longevity per year of schooling of a statistical person discounted to age 18 with a rate of 3.5% is about $100,000, which exceeds the total cost of college by $13,000, but less conservative estimates give an even larger gap. Indeed, according to the College Board, an average cost of a public college for state residents in 2013-14 is about $9,000, while many students at private schools receive scholarships.

Figure 6: Life Expectancy by Personality and Education, Males



Notes: Life expectancy at birth is conditional on survival to age 30. Changes with respect to each personality skill are shown while keeping all other skills at their average levels. Calculations are based on the Terman data.

the average level. I present results for three skills that show a statistically significant effect: Conscientiousness, Extraversion, and Cognition. The differences in life expectancy between the ninth and the first deciles of skills are substantial: about 6 years for Conscientiousness, 5 years for Extraversion, and 2 years for Cognition. The evaluations of longevity differences for a statistical person in thousands of US dollars are about 650, 550, and 200.[43] Since the dependencies are close to linear, an improvement by one decile corresponds to about 0.75 years for Conscientiousness, 0.63 years for Extraversion, and 0.25

[43]See Figure M-15 and its description in the Web Appendix.

years for Cognition, with value for a statistical person equal to 81, 69, and 25 thousand USD respectively.[44] Thus, an early intervention performed by parents or educators that by age 12 improves productive psychological skills by one decile is expected to lead to substantial longevity benefits later on.

All curves in Figure 6 are parallel except for one curve. The parallelism represents the lack of interactions between education and personality skills. The line that is not parallel to the others represents life expectancy by Conscientiousness for Doctorates (see panel (a)). While slopes of all other lines are statistically significant, we cannot distinguish the slope of the line for Doctorates from zero, implying that future doctorates do not benefit in terms of longevity from additional childhood Conscientiousness so that the longevity returns to Doctorate degree decline with Conscientiousness.[45] This result is in line with Conti et al. (2011), who found a negative interaction between education and a Conscientiousness-related personality skill in predicting a number of health behaviors.

I offer two possible explanations for the observed decline of the effect of the Doctorate degree with childhood Conscientiousness. First, knowledge, lifestyles, and earnings that come with a Doctorate degree promote healthier behaviors and health investments, which compensate for somewhat lower adult Conscientiousness, which comes as a consequence of lower childhood Conscientiousness. This explanation is consistent with evidence based on the same data of the strong effect of Doctoral education on wages and the number of memberships in organizations (Savelyev and Tan, 2014).[46] The

[44]These are present values of the value of additional longevity induced by changing skills by one decile for a statistical person.

[45]See Figure M-17 of the Web Appendix showing average effects of doctorate education by Conscientiousness. While for the first decile the effect of a Doctorate degree is statistically significant at 14 additional years of life, for the ninth decile the effect is borderline statistically significant at six years.

[46]A number of other important behaviors that were probably affected by a Doctorate degree, such as smoking, were either not observed in the Terman data or were measured only

second explanation is that the process of obtaining doctoral education helps develop adult Conscientiousness, so that people with low childhood Conscientiousness develop more additional Conscientiousness than people who were already conscientious. The Terman data are not suitable for testing this second possible explanation because of the lack of comparable measures of personality across ages, but this assumption is in line with growing evidence of the malleability of personality skills over the lifecycle (see Almlund et al. (2011) for a survey).

Comparison with the Literature I compare estimates of the effect of college education on an aggregated measure of mortality, which is similar to the measure used in Buckles et al. (2013). Table 2 shows a remarkably close agreement between the most preferred 2SLS results by Buckles et al. (2013) and my calculations based on different data and methodology.

Table 2: Effect of College Degree on Mortality per 1000 Population, Males

	Buckles et al. (2013)	This paper		
Average age over the risk period	(A) 46.5	(B) 50.5	(C) 52.5	(D) 54.5
The effect of college	-94 ***	-102 **	-99 **	-98 **
Standard error	(26)	(40)	(41)	(43)
Sample size	600	629	625	623
Duration of the mortality risk period	27	27	27	27
Age at the beginning of the risk period	28–39	32–42	34–45	36–47
Age at the end of mortality risk period	54–65	58–69	60–71	62–73
Mortality risk period	1981–2007	1947–1973	1949–1975	1951–1977
Population	white males of the general US population	white males with high IQ from California		
Cohorts	1942–1953	1904–1915		
Age range in the cohorts	12	12		

Notes: Panels (A) and (B) present the cubic-2SLS estimate from Buckles et al. (2013) and the most comparable model of this paper. Panels (C) and (D) contain robustness checks.

late in the panel, at which time surviving respondents were 70–80 years old.

Such a close match may not be expected ex-ante given the different ages of birth (1904–15 vs. 1942–53) and different levels of the average IQ (149 vs. 100), but it is possible that factors associated with higher IQ and factors associated with the earlier cohort about cancelled each other out.[47]

To further discuss Table 2, there are many similarities between the cohort used by my paper and that used by Buckles et al. (2013) documented in the table. There is one complication though. The risk period in Terman that corresponds to the same age range as in the Buckles et al. paper starts in the middle of World War II, a period that includes additional risks for mortality even outside battlefields, such as merchant ships sunk by submarines or weapon-related accidents. To account for this problem, I shift the starting year of observations a few years further to 1947. I make a robustness check using two further shifts towards older ages shown in panels (C) and (D), and find that small shifts like this have negligible effects on the estimate.

Data Limitations and External Validity Economists usually study data sampled from the general population, but the Terman data are still informative for a number of reasons. First, the effect of education on health may differ with the level of IQ, and this paper allows us to explore the limiting case when IQ is high and to verify claims made in the literature. Contrary to Auld and Sidhu (2005), who use parental education as an IV and claim that schooling has a large effect on health "only for individuals who obtain low levels of schooling, particularly low-ability individuals" and that "years of schooling beyond high school contribute very little to health," I find that college edu-

[47]We can see a similar cancelling out in panel (b) of Figure J-1 of the Web Appendix, in which Vietnam War generation (born about 1940–50) life expectancy curves approach such a curve for the Terman cohort (born about 1910) from below. Moreover, as I showed in the Web Appendix I, static approach to life expectancy calculation leads to a downward bias of about three years at age 30. The Vietnam War generation survival curves corrected for the bias (not shown) are even closer to the Terman survival curve.

cation strongly increases longevity even for individuals with extraordinarily high ability. Second, having a sample of high IQ subjects allows me to study effects on longevity of all education levels up to a Doctorate degree without worrying about a confounding effect of IQ: all participants had enough cognitive potential to receive a Doctorate, a property that only holds in a sample selected on high ability. Finally, I argue that even though the main results of this paper are obtained for men with extraordinarily high IQs, the results are likely generalizable to a much broader population of men who are smart but not necessarily extraordinarily smart, since good choices of beneficial health behaviors such as healthy diet or regular physical exercise, which are powerful mechanisms of longevity production, do not require an extraordinary cognitive talent. With a number of limitations, I also argue in favor of generalizing the results of this paper to contemporary cohorts of males (see Web Appendix L for more details.)

Comparison to Alternative Cox Model Specifications I compare alternative Cox Model specifications for males in Table 3 for the analysis of model robustness to alternative specifications and its sensitivity to misspecification.[48]

Coefficients of my most preferred Cox model of mortality hazard are tabulated in panel 1a.[49,50] A comparison with a similar model based on teachers'

[48]Table 3 shows estimates for the main variables only. Estimates for background controls and for the measurement system are presented and described in the Web Appendix (see Tables M-4 and M-5). Unlike for males, the hypothesis that the Cox regression coefficients are jointly zero cannot be rejected for females, and therefore I placed the corresponding Table for females to the Web appendix as less informative (see Table M-6).

[49]As discussed above, conditioning on survival through age 30 is motivated by observed completion of education by that age by almost all subjects, which makes education a past event. In Tables M-7–M-8 of the Web Appendix I show that the results of the model are robust to the choice of such age: regression coefficients and p-values for models with initial ages of 40, 50, and 60 are similar.

[50]A simplification of model 1a, in which I do not control for education and interaction between Doctorate and Conscientiousness, is still in line with the main results showing effects of Conscientiousness and Extraversion for males but not for females (see Table M-9 of the Web Appendix).

Table 3: Cox Proportional Hazard Model of Mortality, Males

	Teachers' and Parents' Ratings[(a)]			Teachers' Ratings[(b)]			Parents' Ratings[(c)]			No control for personality		PH test p-values[(d)]
	1a	2a	3a	1b	2b	3b	1c	2c	3c	4	5	
Education												
High school	0.730 ***	0.688 ***	0.808 ***	0.734 ***	0.704 ***	0.827 ***	0.724 ***	0.715 ***	0.785 ***	0.701 ***	0.753 ***	0.537
	(0.193)	*(0.193)*	*(0.181)*	*(0.194)*	*(0.203)*	*(0.193)*	*(0.197)*	*(0.203)*	*(0.185)*	*(0.194)*	*(0.183)*	
Some college	0.310 **	0.291 *	0.351 **	0.340 **	0.335 **	0.399 ***	0.308 *	0.322 **	0.361 **	0.361 **	0.432 **	0.618
	(0.154)	*(0.153)*	*(0.148)*	*(0.150)*	*(0.165)*	*(0.143)*	*(0.158)*	*(0.157)*	*(0.154)*	*(0.146)*	*(0.142)*	
Bachelor's or Master's degree	–	–	–	–	–	–	–	–	–	–	–	–
	–	–	–	–	–	–	–	–	–	–	–	
Doctorate degree	-0.084	-0.112	-0.191	-0.109	-0.174	-0.207	-0.093	-0.095	-0.171	-0.108	-0.168	0.761
	(0.147)	*(0.148)*	*(0.144)*	*(0.148)*	*(0.157)*	*(0.167)*	*(0.144)*	*(0.148)*	*(0.139)*	*(0.140)*	*(0.135)*	
Psychological skills												
Conscientiousness	-0.189 **	-0.165 **	-0.320 ***	-0.194 **	-0.149 **	-0.282	-0.128	-0.123 *	-0.229 **	–	–	0.306
	(0.079)	*(0.069)*	*(0.089)*	*(0.081)*	*(0.073)*	*(0.212)*	*(0.088)*	*(0.070)*	*(0.094)*	–	–	
Conscientiousness × Doctorate	0.249 *	0.212	0.394 **	0.296 **	0.277 *	0.430 **	0.124	0.096	0.196	–	–	0.875
	(0.147)	*(0.135)*	*(0.155)*	*(0.144)*	*(0.143)*	*(0.189)*	*(0.161)*	*(0.138)*	*(0.157)*	–	–	
Extraversion	-0.152 **	-0.112 *	-0.101	-0.073	-0.027	-0.026	-0.163 *	-0.128 **	-0.126	–	–	0.340
	(0.063)	*(0.060)*	*(0.075)*	*(0.077)*	*(0.064)*	*(0.076)*	*(0.084)*	*(0.064)*	*(0.079)*	–	–	
Openness	0.071	0.048	0.173 *	0.093	0.042	0.136	0.067	0.047	0.142	–	–	0.304
	(0.076)	*(0.062)*	*(0.090)*	*(0.083)*	*(0.068)*	*(0.144)*	*(0.089)*	*(0.062)*	*(0.088)*	–	–	
IQ, ages 30-50	-0.447 **	-0.444 **	–	-0.446 **	-0.509 **	–	-0.449 **	-0.492 **	–	-0.445 **	–	0.186
	(0.213)	*(0.212)*	–	*(0.213)*	*(0.231)*	–	*(0.215)*	*(0.241)*	–	*(0.215)*	–	
IQ, above age 50	0.020	0.022	–	0.023	0.016	–	0.020	0.012	–	0.027	–	0.242
	(0.064)	*(0.064)*	–	*(0.065)*	*(0.071)*	–	*(0.064)*	*(0.065)*	–	*(0.064)*	–	
Background Variables	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	No	–
Joint test *p*-value[(e)]	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.347
Sample size	680	680	680	680	680	680	680	680	680	680	680	680

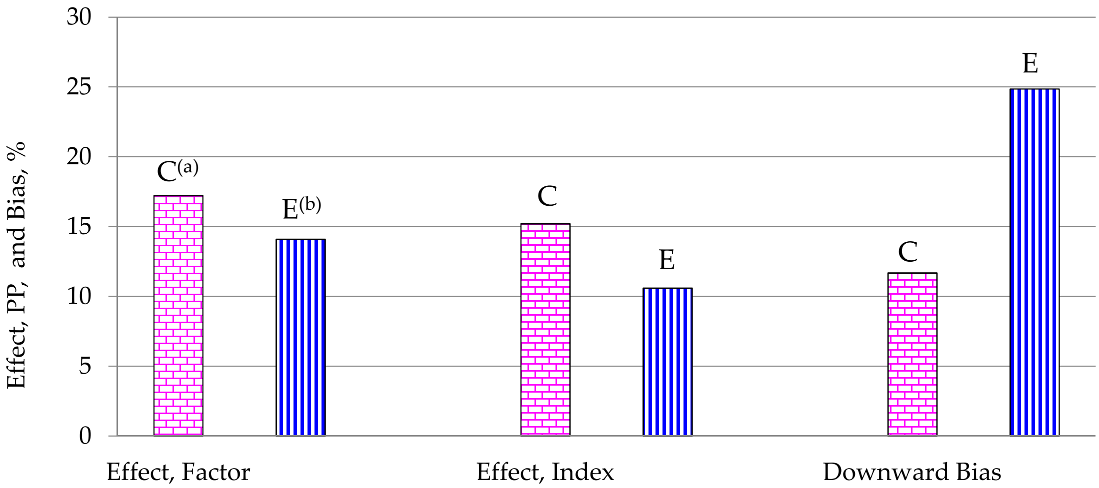
Notes: Model 1a is the most preferred model. [(a)]Personality skills are measured based on averaged ratings of the same skills independently made by the teacher and the parents of the child; [(b)]only teacher's ratings used; [(c)]only parental ratings used; [(d)]to test the proportional hazard assumption, I perform the Wald test. I allow the coefficient in question to differ for every ten-year period, and then test if coefficients are the same across time. A ten-year period is chosen from practical considerations given sample size of 680. [(e)]Test if all listed coefficients are zero (except for the joint PH test in the last column, which is the union of all individual PH-tests). Models 1a, 1b, and 1c are versions of the main factor model. Models 2a, 2b, and 2c are corresponding models using an index (averaged measures) instead of latent factors. Models 3a, 3b, and 3c are versions of the main factor model without controlling for IQ and $\boldsymbol{X}$. Model 4 controls for IQ but not personality. Model 5 controls for education only.

and parents' ratings (models 1b and 1c) reveals that the causal effects of education and IQ are robust to the type of rater, while effects of personality skills show some differences. In particular, while signs of estimated coefficients are robust to the choice of rater, estimates and standard errors vary. A likely interpretation of this result is that teachers and parents see children in different environments, which may induce differences in answers. For instance, the side of extraversion that teachers may observe in class (say, love for socializing, which is not always productive for learning) could be less predictive for longevity than the side of extraversion that parents observe (say, leadership and good relationships with friends). As in previous research based on the same data (Friedman et al., 2010, 1995, 1993), I average ratings for my best estimates to account of all available sources of information. This approach is in line with Murray et al. (2007), who conclude that obtaining ratings from multiple informants is critical for obtaining a full picture of children's functioning.

A comparison of the most preferred model's 1a estimates with estimates based on the less preferred model (2a) shows biases that are induced by ignoring the factor-analytic method as a way to control for measurement error in measures.[51] Unlike a factor model, an equally-weighted average of measures, which I call here "an index," only partly controls for measurement error by diminishing it through averaging. When the number of measures to be averaged is small, using an index is associated with a substantial attenuation bias, which I show in this paper. I demonstrate biases of 12–25% in Figure 7, which shows two direct effects of personality skills on the hazard of death that are statistically significant, namely effects of Conscientiousness (for education below Doctorate) and Extraversion. I also find that the bias due to omission of

[51] See Figure M-18 of the Web Appendix for the share of measurement error in measures, which is, typically, about 50–70%.

Figure 7: Alternative Estimates of the Effects of Skills on the Hazard of Death and the Attenuation Bias, Males



Notes: Effects show a percentage change in the hazard of death in response to one standard deviation increase in skill. Letters denote: [(a)]C, Conscientiousness; [(b)]E, Extraversion. The graph compares statistically significant effects of psychological skills calculated based on the Cox model 1a (with latent factors) and Cox model 2a (with an equally-weighted average of measures (indicies)). See Table 3 for estimated coefficients of models 1a and 2a.

personality controls can also be substantial.[52]

5 Conclusions

In line with the emerging literature in economics of human development, this paper explicitly accounts for latent psychological skills in order to investigate causal relationships between psychological skills, education, and longevity. To obtain the results, I use concepts and methods from psychometrics, a discipline at the forefront of measuring psychological skills.

I apply these tools to a widely recognized, but still largely unsolved, problem in health economics: the causal effect of education on longevity. I find

[52]See Web Appendix K for a discussion of the omitted variable bias.

a strong causal effect for males but not for females. Additionally, I find direct effects of Conscientiousness, Extraversion, and IQ on longevity of males, while for females I find an effect only for IQ. In addition, Conscientiousness in males interacts with a Doctorate degree in affecting longevity.

The causal effect of education on health and longevity has standard implications for positive education subsidies in cases where education investments are at sub-optimal levels. The effects of Conscientiousness and Extraversion, however, suggest a new dimension for public policy: encouraging the development of children's Conscientiousness and Extraversion at home and at school would contribute to both health and longevity. Additionally, Conscientiousness boosts schooling. Thus, the question of the malleability of Conscientiousness and Extraversion deserves increased research efforts.

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