Diskussionspapierreihe
Working Paper Series

HELMUT SCHMIDT UNIVERSITÄT
Universität der Bundeswehr Hamburg

CHILD HEALTH, HUMAN CAPITAL AND ADULT FINANCIAL BEHAVIOR

MARC-ANDRÉ LUIK

Nr./ No. 174
NOVEMBER 2016

Department of Economics
Fächergruppe Volkswirtschaftslehre

Autoren / Authors

Marc-André Luik
Helmut-Schmidt-Universität Hamburg
Fakultät für Wirtschafts- und Sozialwissenschaften
Holstenhofweg 85, 22043 Hamburg
luik@hsu-hh.de

Redaktion / Editors
Helmut Schmidt Universität Hamburg / Helmut Schmidt University Hamburg
Fächergruppe Volkswirtschaftslehre / Department of Economics

Eine elektronische Version des Diskussionspapiers ist auf folgender Internetseite zu finden / An electronic version of the paper may be downloaded from the homepage:

http://fgvwl.hsu-hh.de/wp-vwl

Koordinator / Coordinator
Ralf Dewenter
wp-vwl@hsu-hh.de

Helmut Schmidt Universität Hamburg / Helmut Schmidt University Hamburg
Fächergruppe Volkswirtschaftslehre / Department of Economics
Diskussionspapier Nr. 174
Working Paper No. 174

Child Health, Human Capital and Adult Financial Behavior

Marc-André Luik

Zusammenfassung / Abstract

In this work, utilizing yearly variation between biological siblings, we test for a correlation between poor child health and adult household financial behavior, i.e. risky asset market participation. Using regression and decomposition techniques, we test if this long reach of child health operates through cognitive and non-cognitive skills. Our results indicate a negative correlation of roughly -4.1 percentage points conditional on demographics and family background. Slightly more than half of this correlation can be explained by differences in cognitive and non-cognitive skills. This work highlights the importance of good child health for adult financial behavior.

JEL-Klassifikation / JEL-Classification: D14, I1, J24, G11

Schlagworte / Keywords: Portfolio choice, human capital, child health

I would like to thank Michael Berlemann, Deborah Cobb-Clark, Riley Cunningham, David Love, Line Møller Grosen, Jan Salland, Torsten Santavirta, Thomas Siedler, Bettina Siflinger, Max Steinhardt, Dennis Wesselbaum as well as the seminar and conference audience at the University of Hamburg, Helmut Schmidt University and Spring Meeting of Young Economists 2016 in Lisbon for many useful comments and suggestions.

1. Introduction

Research collected considerable empirical evidence in favor of a long reach of child and adolescent health (e.g. Oreopoulos et al., 2008; Lundborg et al., 2014). This literature indicates that poor child health predicts inferior adult socio-economic status (SES)[1], commonly measured by education, income and occupation. A related strand of literature shows that poor child health is more prevalent in families of lower parental socio-economic status (Case et al., 2002; Currie and Stabile, 2003). According to Currie (2009), this suggests that child health could be a driver of the intergenerational transmission of SES.

But why is there a long reach of child health on adult SES? Maybe the most intuitive explanation is its detrimental impact on future adult health capacity and health behavior (Case et al., 2005; Kesternich et al., 2015). As poor health can inhibit work load, it might lower labor market outcomes, such as occupational choice, labor supply or earnings (Smith, 1999). According to Smith (2009a), assortative mating on the marriage market might amplify this effect on the household level. This, in turn, has important implications for level and growth of household income and wealth.

A very appealing explanation, however, takes place (mostly) before entering adulthood. Adverse early-life health can inhibit skill formation throughout childhood via health impairment and school absence (Currie, 2009). These skill differences open up early, persist over the adult lifecycle and predict a wide array of adult outcomes (Heckman et al., 2006). More generally, the interplay of child health and skills has been formalized in the skill formation model of Cunha and Heckman (2007). Therefore, we would expect a correlation between child health and any adult outcome that is also influenced by human capital, such as labor market outcomes (Becker, 1975; Smith, 2009a).

An underexplored dimension of adult SES is household finance. In this paper we analyze if poor child health is related to adult financial behavior, i.e. risky asset market participation. Non-participation is one of the stylized facts of household finance (Haliassos and Bertaut, 1995) and can have adverse effects on retirement preparation and future consumption (Cocco et al., 2005). Hence, it can act as a multiplier to

[1] The U.S. National Center of Education Statistics defines SES in the following way: "SES can be defined broadly as one's access to financial, social, cultural, and human capital resources. Traditionally a student's SES has included, as components, parental educational attainment, parental occupational status, and household or family income, with appropriate adjustment for household or family composition. An expanded SES measure could include measures of additional household, neighborhood, and school resources."

the intergenerational SES and inequality transmission channel *child health*. For the first time, we deliver empirical evidence based on yearly variation between biological siblings and test to what extent this relationship can be explained by differences in human capital (skills). In particular, we test two hypotheses derived from portfolio choice with human capital (Bodie et al., 1992) and skill formation theory (Cunha and Heckman, 2007) using the National Longitudinal Study of Youth 1979 (NLSY79): first, poor child health has a negative correlation with adult risky asset market participation which, second, can be explained with disrupted skill formation throughout childhood.

Our results from yearly sibling fixed effects regressions indicate a negative correlation between poor child health and adult risky asset market participation. Conditional on demographics and parental SES we find poor child health to be associated with a 4.1 percentage points (pp) decrease in the participation likelihood. In line with our second hypothesis, we find cognitive (44%) and non-cognitive (17%) skills to explain sizable shares of this relationship. Factors such as educational attainment, adult health and total household labor income play only a limited role in explaining the remaining correlation of roughly -2 pp. The same pattern is also found excluding yearly sibling fixed effects. Consequently, child health seems to affect financial behavior rather through skills than through unobserved family background characteristics. Our results are robust to differential parental treatment of siblings and remain very similar in OLS and Logit specifications.

.

The study contributes to different research strands. We are the first to extend the literature on long-run effects of child health using sibling designs by looking at financial behavior, i.e. risky asset market participation. From a technical point of view, to the extent of our knowledge, we are also the first to apply yearly sibling fixed effects regressions in the field of household finance.[2] This methodology should be increasingly useful to tackle unobserved family background heterogeneity and address variables with little (or no) variation over time (in the abundance of twins) (Calvet and Sodini, 2014). Finally, we contribute to the growing literature on cognitive and non-cognitive skills in household finance. In particular, we focus on skill origin and embed it in a life course context motivated by portfolio choice with human capital and skill formation

[2]However, there have been recent applications of yearly twin fixed effects (Calvet and Sodini, 2014) and sibling fixed effects (Kuhnen and Melzer, 2015) in the context of the risky share of financial wealth and loan delinquency.

theory.

The structure of the article is as follows. Section two presents the related literature. In section three we present the theoretical motivation. In chapter four we describe the underlying dataset and variable construction. Moreover, we offer first descriptive statistics. Section five sketches our empirical strategy, key results and robustness checks, while section six sums up our results.

2. Related Literature

The related empirical evidence on the role of individual-specific child conditions for adult financial behavior is comparatively small. Using the Survey of Health, Ageing and Retirement in Europe (SHARE), Christelis et al. (2012) test if retrospectively reported childhood conditions are associated with adult risk-taking conditional on education, adult income and wealth. While they find subjective relative school performance and parental SES to be predictors of adult asset demand, poor childhood health plays only a minor role. Using European and U.S. survey data, Addoum et al. (2015) show that physical attributes, like relative adult height and weight, are correlated with stockholding. As child and adult height tend to be correlated, height is an often-used general proxy for health and nutrition in early-life (Case and Paxson, 2008). Approximating prenatal conditions among Swedish Twins, Cronqvist et al. (2016) find that the twin with higher birth weight is more likely to hold risky assets. Turning to the prenatal environment, they find that females with a male co-twin take more financial risk in adulthood than females with a female co-twin. Their results indicate that most of the relationships run via investor preferences (direct) and adult SES (indirect).

Other related research addresses the role of child environment. For instance, there is empirical evidence from the U.S. that the early-life business cycle stage (Malmendier and Nagel, 2011) and kindergarten (Chetty et al., 2011) shapes later financial risk-taking and retirement savings, respectively. Keister (2003) analyzes the relationship between number of siblings and adult wealth ownership using the NLSY79. Assuming that siblings are less likely to receive parental investment in larger families, she finds sibship size to have a negative association with stock/home ownership and inheritance receipt. The relative importance of child environment and genetic heritage is also called the "nature vs nurture" debate. Using Panel Study of Income Dynamics (PSID) data from the U.S., Chiteji and Stafford (1999) find a correlation between the portfolios of parents and offsprings during young adulthood. They, thereby, stress the importance to experience different financial options in early-life. However, part of this correlation could still be driven by genetic heritage. Black et al. (2015) use Swedish data on adoptee, adoptive and biological parents and find that only financial behavior of adoptive parents, and thus the environment, explains offspring financial outcomes. In contrast to this, Cesarini et al. (2010) and Barnea et al. (2010) find that roughly 30% of Swedish variation in portfolio behavior can be explained by genetic variation.

Lastly, there is compelling evidence validating the theoretical relationship between human capital and portfolio choice (Bodie et al., 1992). Vissing-Jorgensen (2002) and Calvet and Sodini (2014) confirm the positive theoretical relationship between human capital (discounted future income) and financial risk-taking using U.S. data from the PSID and Swedish register data on twins. Other works affirmed the positive relationship between human capital and financial risk-taking using Cunha and Heckman (2007)'s cognitive (Christelis et al., 2010; Grinblatt et al., 2011; Agarwal and Mazumder, 2013) and/or non-cognitive skills (Hong et al., 2004; Luik and Steinhardt, 2016)[3], or education (Campell, 2006; Cole et al., 2014).

3. Theoretical Motivation

In the following section we use two distinct and well-established theories regarding (child) skill formation (Cunha and Heckman, 2007) and (adult) portfolio choice (Bodie et al., 1992) to derive our research hypotheses.

3.1. Skill Formation

This section outlines the core properties of the skill formation model by Cunha and Heckman (2007) and applies it to the case of poor child health. Θ_t is a vector of skills for each childhood stage t. The next period's vector of skills depends on the current production function f_t and its input vectors: parental skills

[3]With regards to non-cognitive skills, research is still in an early stage. An exception is the seminal work by Hong et al. (2004) who show that sociability determines stock market participation. Kuhnen and Melzer (2015) find that self-efficacy is negatively associated with financial distress, including delinquency on loans, repossession of assets and lost access to credits. Luik and Steinhardt (2016) study the immigrant-native stock market participation gap in the U.S. and find cognitive and non-cognitive skills to be determinants of stockholding and gap drivers. While the empirical evidence is based on specific cognitive and non-cognitive skills, the model of Cunha and Heckman (2007) refers to a range of latent cognitive and non-cognitive skills.

h, child's skills Θ_t and parental investment I_t. Put differently, the level of skills depends on environment, investment and genes. The general relationship is formalized in equation 1.

$$\Theta_{t+1} = f_t(h, \Theta_t, I_t). \tag{1}$$

As technology varies over time, some stages might be more productive than others in producing a certain skill or processing particular inputs. While productive periods are called "sensitive", a single productive period for creating a skill is called "critical" (Cunha and Heckman, 2007).

Skill formation has two additional "multiplying" intertemporal mechanisms. First, the level of currently attained skills augments the production of future skills. This "self-productivity" implies self-enforcing and persistent effects of acquired skills and disruptions (equation 2).

$$\frac{\partial f_t(h, \Theta_t, I_t)}{\partial \Theta_t} > 0. \tag{2}$$

Second, currently produced skills foster the productivity of future investments (equation 3). As a result, this "dynamic complementarity of investment" leads to bolstering investment at different ages. According to Cunha and Heckman (2007), this stresses the need to follow up early investments. Ultimately, these two mechanisms form a multiplier in which "skills beget skills" and rationalize why returns to later remediations are lower than early-life interventions.

$$\frac{\partial^2 f_t(h, \Theta_t, I_t)}{\partial \Theta_t \partial I_t'} > 0. \tag{3}$$

Thus far, we have ignored the content of our skills vector Θ_t. In the broadest possible abstraction, Cunha and Heckman (2007) distinguish between two vectors of cognitive C and non-cognitive N skills. Each individual uses them with varying weights depending on the specific situation. Both skills have been shown to predict a variety of adult outcomes (Heckman et al., 2006). Replacing the skill vector by these components and allowing skill-specific investment in equation 1, we arrive at equation 4. Each other's production is then affected by the levels of cognitive and non-cognitive skills. Therefore, self-productivity also has a cross-fertilizing dimension. For instance, a higher level of non-cognitive skills, like conscientiousness or farsightedness, could be beneficial for the accumulation of cognitive skills, while an increased endowment of cognitive skills could positively affect non-cognitive skills, such as self-esteem or locus of control.

$$\Theta_{t+1}^k = f_t^k(h^k, \Theta_t^k, I_t^k), k \in C, N. \tag{4}$$

Crucial to our work, this framework can be extended to include health capacity H (Heckman, 2007; Currie and Almond, 2011). Equation 5 formalizes cross-productivity effects between both skills and health capacity. For example, one could imagine that poor health inhibits skill formation due to either health impairment or social exclusion (Currie, 2009). However, one could also think of certain cognitive and non-cognitive skills driving risky health behavior via their impact on risk and time preferences (Cunha and Heckman, 2007).

$$\Theta_{t+1}^{k} = f_t^k(h^k, \Theta_t^k, I_t^k), k \in C, N, H. \tag{5}$$

Hence, skill formation theory suggests that poor child health is associated with persistent lower cognitive and non-cognitive skill formation.

3.2. Portfolio Choice

In traditional portfolio choice theory (Samuelson, 1969; Merton, 1969) the optimal share α of financial wealth FW_t invested in risky assets depends on risk aversion γ, risk σ^2 and return μ of risky assets (equation 6). As a consequence, in their framework each investor should hold a positive and constant risky fraction of financial wealth.

$$\alpha = \frac{\mu}{\gamma \cdot \sigma^2}. \tag{6}$$

This solution, however, ignores human capital (human wealth), which is usually understood as an illiquid asset equal to discounted future labor income. This human capital is on average the single largest wealth component and often compared to a non-traded bond (Calvet and Sodini, 2014). Introducing riskless human capital HC_t to the portfolio choice optimization problem (equation 7), $\frac{\mu}{\gamma \cdot \sigma^2}$ now captures the optimal risky share of total wealth $FW_t + HC_t$ (Bodie et al., 1992). In contrast to equation 6, the optimal risky share of financial wealth is larger (assuming positive human capital) and time-variant.[4] Accordingly, ignoring human capital results in suboptimal portfolio allocation.

$$\frac{\alpha_t \cdot FW_t}{FW_t + HC_t} = \frac{\mu}{\gamma \cdot \sigma^2}. \tag{7}$$

[4]For constant values of financial wealth, decreasing lifecycle future income streams and human capital introduce share variation over time. As a consequence, the optimal financial portfolio is tilted towards safer assets over the lifecycle. Drivers of this process are decreasing years of remaining work life and labor supply flexibility to offset financial risks (Bodie et al., 1992).

As formalized by equation 8, investors with more human capital should invest a larger share of their financial wealth in risky assets.[5]

$$\frac{\partial \alpha_t}{\partial HC_t} = \frac{\mu}{\gamma \cdot \sigma^2} \cdot \left[\frac{1}{FW_t} \right] > 0. \tag{8}$$

While traditional portfolio choice theory suggests that all individuals should participate in risky assets, it is a well-established empirical fact that the majority of individuals and households does not hold any risky assets (Haliassos and Bertaut, 1995). This non-participation holds true even though research suggests adverse welfare impacts through future wealth accumulation and consumption (Cocco et al., 2005). Within the extensive amount of literature on determinants of risky asset market participation, perhaps the broadest consensus in terms of deterring factors exists in the form of fixed participation, entry or continuation costs. Vissing-Jorgensen (2002) shows that augmenting traditional models by a modest fixed per-period cost can render small optimal investments non-profitable. The same holds true in a dynamic context of time-varying financial wealth. The logic of fixed participation costs is also useful to study the relationship with human capital. A smaller optimal risky share of wealth, driven by lower human capital, decreases the fixed costs required to keep a household out of the market and, accordingly, lowers the likelihood to participate (Haliassos and Bertaut, 1995). [6]

In the context of this work, lower human capital (associated with poor child health) requires the household to invest a smaller share of financial wealth in risky assets. Assuming participation costs, smaller risky asset investments are rendered non-profitable and should therefore increase non-participation among the group of poor child health and low skills. This being the case, we obtain two testable hypotheses: first, there should be a negative correlation between child health and risky asset market participation; second, this correlation should be mostly explained by differences in skills.

[5] As human capital is not entirely riskless, the degree to which human capital tilts the portfolio towards riskier financial assets depends on the correlation between labor income risk and stock returns. While correlation offers hedging opportunities, zero correlation renders the risky share comparatively smaller. In the case of short sales restrictions this is limited to negative correlations (Vissing-Jorgensen, 2002).

[6] However, liquidity or borrowing constraints might keep a household from participating despite its stock of human wealth. Fagereng et al. (2015) formalize this argument in a model with per-period participation costs. In their model households start to enter the stock market as soon as they have accumulated sufficient wealth and as long as they haven't decumulated too much of it in retirement.

4. Data and Descriptive Statistics

4.1. Data

Analysis of correlations between child conditions and adult outcomes requires certain data characteristics. Most notably, respondents should be followed from child- to adulthood. Moreover, these datasets need to cover the adult outcome of interest and a wide range of early-life characteristics. We employ the NLSY79, which tracks U.S. individuals from adolescence in 1979 (14-22) to adulthood in 2012 (47-55). In particular, respondents have been recontacted annually until 1994 and biannually thereafter. It is a well-established dataset containing information on all our areas of interest (Heckman et al., 2006).

While there are datasets with more detailed childhood conditions, these datasets usually lack longitudinal information on financial assets.[7] A popular alternative to the NLSY79 would be the Panel Study of Income Dynamics (PSID). For instance, Smith (2009a) uses offsprings of original PSID respondents to study correlations between retrospective early-life health and labor market outcomes. However, the PSID lacks rich information on cognitive and non-cognitive skills (in adolescence). Skills central to our work makes the PSID unsuitable for this analysis.

4.2. Variables and Dataset Construction

Central to our analysis are measures of early-life health, financial behavior and skills (human capital). In this section we discuss the construction of our variables of interest and benchmark sample.

Crucial to our analysis is the variable for early-life health. Currie (2009) stresses that health is inherently multidimensional and difficult to capture in a single index. Even if the perfect index were available, it might refer to different childhood or adolescent stages which can be critical for the development of various skills. Owing to the abundance of detailed register child health data from the U.S., we employ a retrospective assessment of general child health up to age 17. In 2012, a subset of our respondents is asked to scale their past child and adolescent health: "Consider your health when you were growing up, from birth to age 17. Would you say your health during that time was excellent, very good, good, fair, or poor?". Self-reported childhood health is a well-established and well-behaved proxy in the empirical literature on long-run effects

[7] The British National Child Development Study (NCDS) and the British Cohort Study (BCS) have very detailed information on childhood conditions, related health and adult socio-economic outcomes. In the U.S., the NLSY79YA collects rich information on child- and young adulthood of NLSY79 offsprings. However, all these datasets miss detailed asset information over time.

(e.g. Smith, 2009a). Smith (2009b) showed that respondents to HRS and PSID recall childhood events, such as illnesses, with reasonable quality. Moreover, self-reported health is shown to proxy actual health with sufficient accuracy (Fletcher and Lehrer, 2011).

Our outcome variable of interest is household financial risk-taking. In particular, we are interested in the decision to hold any risky asset. Since 1988, the NLSY79 has been asking for ownership and amount of single wealth components at the household level. However, as the NLSY79 introduced more detailed asset subcategories over time, we harmonize risky and safe liquid financial wealth components according to Angerer and Lam (2009). As there is no detailed breakdown of wealth in 1991, 2002, 2006 and 2010, they are thus excluded from the panel. We flag a household if it holds any positive amount of risky assets including stocks, investment trusts, mutual funds or corporate and government non-savings bonds (for variable definitions see also Table A.1).[8]

In order to test if a potential long reach of poor child health can be explained with skill formation, we follow Heckman et al. (2006) and use three test scores to proxy cognitive and non-cognitive skills in adolescence and very early adulthood. Cognitive skills are measured by the Armed Forces Qualification Test (AFQT) in 1981 (age 16-24). As AFQT test scores are commonly correlated with age of test-taking, we use age-adjusted percentile scores provided by the NLSY79. Non-cognitive skills include the Rotter locus of control (1979: 14-22) and Rosenberg self-esteem (1980: 15-23) test scores. Higher scores translate to higher cognitive skills, a more external locus of control and a higher self-esteem. An individual with external locus of control believes that one's actions have less influence on one's personal outcomes. Finally, all test scores are standardized at mean zero with a standard deviation of one.

We employ information on the family background through standard parental SES measures; these are recorded in 1979 and include total family net income in 1978, father's occupation at age 14, educational attainment of father and mother and region of interview. In order to rule out systematic non-response, we include missing dummies for each proxy of child condition except health. Finally, we supplement family background with constant demographics, such as gender, ethnicity and age. All individual characteristics

[8]Safe assets include checking and savings accounts, money market funds, certificates of deposit, U.S. savings bonds, individual retirement accounts, tax-deferred accounts and personal loans. The main reason to model individual retirement and tax-deferred accounts as being part of safe assets lies in their aggregation with safe assets in earlier waves.

are taken from the survey respondent, whereas financial information is recorded at the household level.

Our benchmark analysis uses household-year observations with information on adult financial assets, (adolescent) skills and child health. We drop the military and poor whites oversamples due to discontinuation after 1984 and 1990, respectively. Ultimately, our benchmark sample includes 6,636 adult household heads from 4,745 families with a total of 75,646 observations from 1988 to 2012.

4.3. Descriptive Results

Throughout our analysis we make use of a full and a sibling sample. The latter is restricted to all respondents, who share the same biological father and mother with at least one other sibling. This reduces the full sample by roughly 52%.[9] Table 1 displays selected descriptive statistics for financial behavior, demographics, parental SES and skills in our full and sibling sample, respectively. Almost one fifth (18%) of all households in our full sample hold some risky asset and 5% rate their child health up to age 17 as poor. Overall, mean statistics are remarkably similar in the full and sibling sample. A noteworthy exception is average family income in 1978, which is 2000 US-Dollars higher in the sibling subsample.

In Figure 1, using the full sample, we display average risky asset market participation per year by child health status. Following the NLSY79 cohort over time, it also approximates an average lifecycle profile for the birth cohort 1957-1964. As a consequence, 1988 and 2012 correspond to ages 23-31 and 47-56, respectively. Households with adverse early-life health history are clearly less likely to hold risky assets. The gap is fairly persistent around 7 to 9 pp. Relative to an average holding rate of 18 % this is substantial. Both groups follow the hump-shaped stockholding lifecycle pattern as suggested by the model of Fagereng et al. (2015).[10]

Using our full sample, Table 2 gives first insights into the bivariate relationships between child health and financial behavior, demographics, family background and skills.[11] In particular, we look at mean group differences between individuals with and without poor child health. We find that household respondents with adverse early-life health are 9 pp less likely to hold risky assets. Among these respondents being nonwhite and female is far more prevalent. In line with the literature, our results also suggest a positive

[9]Our sibling sample contains 36,469 household years.

[10]Results are very similar if we use the sibling sample or specific birth year cohorts.

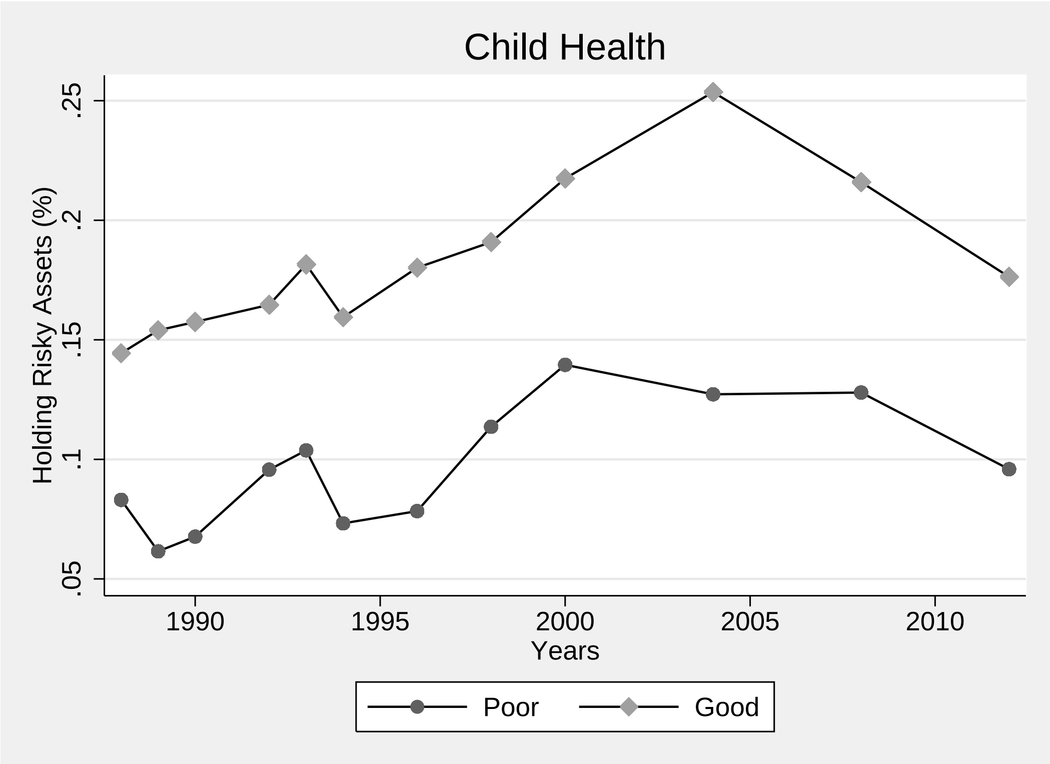
[11]Results are very similar if we use the sibling sample.

Table 1: Descriptive Statistics: Full and Sibling Sample

		(1)			(2)		
		Sample			Sibling Subsample		
	Year	Mean	SD	Count	Mean	SD	Count
Financial Behavior							
Risky Assets (>0)	d	0.18	0.38	75,646	0.19	0.39	36,469
Child Health							
Poor Child Health	e	0.05	0.22	75,646	0.04	0.20	36,469
Demographics							
Age	d	35.75	7.72	75,646	35.46	7.64	36,469
Hispanic	a	0.18	0.39	75,646	0.18	0.38	36,469
Black	a	0.31	0.46	75,646	0.30	0.46	36,469
Non-Hispanic/Non-Black		0.51	0.50	75,646	0.52	0.50	36,469
Male	a	0.47	0.50	75,646	0.50	0.50	36,469
Parental SES							
Educational Attainment (Father)	a	10.96	3.96	64,729	10.97	4.11	32,187
Educational Attainment (Mother)	a	10.85	3.21	71,325	10.93	3.22	34,446
Father White-Collar at Age 14	a	0.28	0.45	52,247	0.29	0.45	26,594
Family Income in 1978	a	17,097.07	13,006.32	61,536	19,068.63	13,652.65	30,426
Skills							
Cognitive Skills: AFQT (Std.)	c	0.00	1.00	75,646	0.03	1.02	36,469
Non-Cognitive Skills: Rosenberg Self-Esteem (Std.)	b	-0.00	1.00	75,646	-0.02	1.00	36,469
Non-Cognitive Skills: Rotter Locus of Control (Std.)	a	0.00	1.00	75,646	0.03	1.00	36,469

Notes. Pooled statistics are based on all observations with information on asset ownership, child health and (non)cognitive skills. Cognitive skills are derived from the AFQT Battery. Self-esteem and external locus of control rely on the Rosenberg and Rotter score. (Non)cognitive skills scores are standardized. The sibling sample is limited to respondents who share the same biological father and mother with at least one other respondent from the original household. Year(s) of recording is (are) denoted by a (1979), b (1980), c (1981), d (1988-2012) and e (2012).

Figure 1: Descriptive Statistics: Child Health Status and Adult Financial Behavior



correlation between parental SES and child health (e.g. Case et al., 2002; Currie and Stabile, 2003). Critical to our analysis, skills are lower among respondents with poor child health. In particular, the scores indicate lower cognitive skills, lower self-esteem and a more external locus of control.

5. Empirical Analysis

Our main empirical analysis is subdivided into four sections: first, we discuss our estimation framework; second, we estimate the total correlation between child health and adult financial behavior; third, we test if skills or alternative explanations are able to explain this relationship; finally, we conduct a range of robustness exercises.

5.1. Empirical Issues and Estimation Framework

Even though we have a rich longitudinal set of information spanning from adolescence to middle adulthood the choice of empirical identification strategy is crucial.

Table 2: Descriptive Statistics: Mean Differences by Child Health Status

	Difference	No Poor Child Health	Poor Child Health
Financial Behavior			
Risky Assets (>0)	0.09***	0.18	0.10
Demographics			
Age	0.24	35.76	35.52
Hispanic	-0.05***	0.18	0.23
Black	-0.04***	0.31	0.34
Non-Hispanic/Non-Black	0.09***	0.51	0.42
Male	0.12***	0.47	0.36
Parental SES			
Educational Attainment (Father)	1.21***	11.02	9.82
Educational Attainment (Mother)	1.03***	10.90	9.87
Father White-Collar at Age 14	0.15***	0.29	0.14
Family Income in 1978	4,904.02***	17,343.80	12,439.79
Skills			
Cognitive Skills: AFQT (Std.)	0.44***	0.02	-0.41
Non-Cognitive Skills: Rosenberg Self-Esteem (Std.)	0.32***	0.02	-0.30
Non-Cognitive Skills: Rotter Locus of Control (Std.)	-0.27***	-0.01	0.26

Notes. Pooled statistics are based on all observations with information on asset ownership, child health and (non)cognitive skills in 1979-1981 and 1988-2012. Cognitive skills are derived from the AFQT Battery in 1981. Self-esteem and external locus of control rely on the Rosenberg (1980) and Rotter (1979) score. (Non)cognitive skills scores are standardized. * p<0.1, ** p<0.05, *** p<0.01

Child health and adult financial behavior, for instance, could both be associated or even caused by a range of family characteristics, including observables, such as parental income, as well as unobservables, such as upbringing. However, in order to identify the unbiased effect of child health, a regression needs to account for all relevant family and non-family characteristics, such that child health is not correlated with our error term.

Equation 9 formulates a pooled regression approach for the household respondent i decision to hold risky assets $s_{i,t}$ in year t. We are interested in the estimate of coefficient β capturing the sensitivity of risky asset participation to the respondent's child health h_i. Coefficient vector γ includes the elasticity of risk-taking to a benchmark set of controls $x_{i,t}$, including ethnicity, sex, and age at interview date. Finally, a_t denotes yearly fixed effects, c is a constant and $\epsilon_{i,t}$ is an error term.

$$s_{i,t} = c + \beta h_i + \gamma' x_{i,t} + a_t + \epsilon_{i,t}. \tag{9}$$

This estimate captures a benchmark correlation purged by demographics determined at conception and yearly fixed effects. As mentioned earlier, particularly at the family level, there are factors likely to be associated with both child health and adult risk-taking. For instance, there is empirical evidence in favor of parental SES affecting child health (e.g. Case et al., 2002) and offspring financial behavior (Chiteji and Stafford, 1999). Drawing on the rich set of information on NLSY79 families from 1979, we could extend our set of controls $x_{i,t}$ by the parental SES proxies fraternal education, maternal education, family income, fraternal occupation and region of interview. If these controls capture some of the unobserved heterogeneity between household respondents, this would provide a less biased estimate of the true effect. Despite this, our relationship of interest could still be confounded by other unobserved family or non-family characteristics, such as cognitive and non-cognitive skills.

A promising approach to account for unobserved family heterogeneity is to exploit differences between siblings who share the same biological parents h. In general, siblings (even more so twins) share the same family background, similar genetics and tend to communicate more often than two random households (Calvet and Sodini, 2014). Consequently, unobserved heterogeneity should be smaller among siblings. As a by-product, this setup allows the analysis of time-constant or highly persistent variables on the individual level as long as there is variation between siblings (Calvet and Sodini, 2014). In contrast to household finance, these sibling fixed effects models have been frequently applied in labor and health economics (e.g.

Oreopoulos et al., 2008). In order to exploit the longitudinal feature of our data, one can follow Calvet and Sodini (2014) and include a sibling fixed effect for each adult survey year. These so-called yearly sibling fixed effects are denoted with $a_{h,t}$ and control for all factors common to siblings in a given year from 1988 to 2012. By definition these include common, past and current, family experience, and yearly fixed effects, which capture macroeconomic developments. Equation (10) formalizes this framework for siblings i of parents h.

$$s_{i,h,t} = a_{h,t} + \beta h_{i,h} + \gamma' x_{i,h,t} + \epsilon_{i,h,t}. \tag{10}$$

A very appealing property of this design is that (biological) siblings also share on average half of their genes (Lundborg et al., 2014). This property is imperative as ignoring genetic information in research on health effects results in an omitted variable bias, stemming from substantial genetic components of health or health behavior (Fletcher and Lehrer, 2009). Assuming a large genetic component, we could use Mendellian randomization, the so-called "genetic lottery", to argue in favor of exogenous health variation (Lundborg et al., 2014b; Fletcher and Lehrer, 2011) and, consequently, approach "partial" causality. According to Lundborg et al. (2014b), here it is useful that the genetic component might be even larger in a sibling design as they share only 50% of their genes but most of their environmental influences.[12] In particular, the underlying idea of this process is that a sibling's inheritance receipt of a certain gene inside a family is random and independent from each other. This line of reasoning has, among others, been used to conduct sibling fixed effects regressions with respect to long-run effects of male (adolescent) health, body size and height on SES outcomes (e.g. Lundborg et al., 2014a; Lundborg et al., 2014b).[13]

In order to analyze how much of this effect can be explained by skill formation (Cunha and Heckman, 2007), one can add cognitive and non-cognitive skills to our fixed effects model and compare the estimate of interest. According to Lundborg et al. (2014a), the fixed effects estimate also gives additional insight about the validity of skills as a mediator. They argue that if skills are only correlated with early-life health via a third unobserved variable, most likely related to family background, an inclusion of skills reduces the

[12] We have found only one study to quantify the genetic component of self-reported health. Romeis et al. (2000) report that more than one third of the variation in self-reported health can be explained by heritability.

[13] While in theory this does not necessarily give us the direction of causation, analyzing a correlation between child- and adulthood, we believe that our risk of reverse causation is minimized if we tackle contemporary unobserved heterogeneity. Moreover, Smith (2009b) offers evidence in favor of adult outcomes not affecting retrospective child health.

poor health coefficient estimate far more in a framework without yearly sibling fixed effects. Thus, if skills explain the correlation to a similar degree in both specifications, it is more likely that that the long reach from childhood operates through disrupted skill formation. Accordingly, we will conduct an analysis with and without yearly sibling fixed effects.

It is important to consider potential caveats of sibling fixed effects frameworks, however. Griliches (1979) stresses that measurement errors are more pronounced in sibling models. In the context of linear regressions an attenuation bias can emerge (Angrist and Krueger, 1999), meaning that potential changes in the estimate, after adding fixed-effects, cannot easily be attributed to unobservables. However, if we still find an effect with less precision it strengthens the case of our analysis. Other critiques of this approach stress that siblings are far from being treated identically (Lundborg et al., 2014a). Whereas twins have the advantage of age equality, younger and older siblings can experience different family environments, including composition and financial endowment. If these effects have a long reach to financial behavior they could bias an "omitting" estimate upwards; yet, we do not expect differences in resources to drive our results, as the median sibling spacing in our sample is 3 years.

Even if both siblings experience the same SES they could also be subject to preferential parental treatment or differences in affection. It can be important to account for parental affection, in the case of correlation with the dependent variable, as it might bias the estimate of child health (Smith, 2009a). Ultimately, the direction depends on parental preferences for human capital inequality and thus compensatory or reinforcing human capital investment, which would either bias our effect downwards or upwards. According to Lundborg et al (2014c) and Currie and Almond (2011), there is no empirical evidence in favor of a systematic preferential parental investment with regards to siblings' health or skill endowment to date. However, in our robustness section we address this issue by including indicators for parental affection and birth order. Finally, negative spillovers of poor health could attenuate our estimate of interest.[14]

Our empirical analysis is as follows. We first run a pooled OLS framework on the full and sibling sample to obtain a benchmark correlation and check for sibling sample selection effects. We then extend our sibling sample specification by family background. In particular, we first control for parental SES

[14] However, one could also imagine that a health spillover is less likely between siblings due to the early exposure to diseases (hygiene hypothesis).

and then add extensive yearly sibling fixed effects.[15] In order to test if disrupted skill formation is the main mechanism behind this correlation, we then include adolescent cognitive and non-cognitive skills one-by-one and altogether. Following this, we offer alternative non-skill explanations for the remaining holding differential including education, preferences and measures of adult SES, i.e. adult health and total household labor income. Finally, we repeat our analysis excluding yearly sibling fixed effects and using decomposition analysis.

5.2. Results: Correlation

The first column of Table 3 reports the estimated correlation between poor child health and adult risky asset market participation based on our full sample. All estimates use a linear probability model with clustered standard errors at the sibling-year level. Using ordinary least squares to estimate long-run effects of child health on binary adult outcomes is widely accepted in the related literature (e.g. Lundborg et al., 2014). This benchmark configuration controls for ethnicity, gender, age at interview and yearly fixed effects. According to Table 3, poor child health seems to be associated with a 7 pp lower likelihood to hold risky assets in adulthood. The estimate of interest is significantly different from zero at the 1% level and the benchmark model captures roughly 5% of the variation in financial behavior. Compared to the overall risky asset market participation of 18% (Table 1) these estimates are substantial and of economic significance. Finally, the model seems to be well-behaved as estimates of quadratic age, ethnicity and sex are significant and in line with the literature (e.g. Haliassos and Bertaut, 1995).

5.3. What explains the correlation?

We have shown a substantial correlation between child health and adult financial behavior. To what extent can this association be explained by early-life factors? As we have discussed in our methodology parental SES and unobserved family background are potentially fruitful explanations. Moreover, motivated by portfolio choice and skill formation theory, we are particularly interested in the role of skills. In order to compare the contribution of each factor, we move to our sibling sample and include each explanation one-by-one. We begin by reestimating our correlation in the sibling sample (column 2). Again, we obtain a

[15] As a consequence of adding yearly sibling fixed effects we drop our "nested" yearly dummies. However, we keep controls for demographics and parental SES as they might differ to a small extent between siblings. For instance, a parent might have attained a higher grade in the meantime.

Table 3: Correlation Between Child Health and Adult Financial Behavior

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Poor Child Health	-0.070***	-0.064***	-0.039***	-0.041***	-0.023**	-0.034***	-0.020*
	(0.005)	(0.007)	(0.007)	(0.011)	(0.011)	(0.011)	(0.011)
Cognitive Skills: AFQT (Std.)					0.087***		0.084***
					(0.005)		(0.005)
Non-Cognitive Skills: Rosenberg Self-Esteem (Std.)						0.019***	0.010***
						(0.003)	(0.003)
Non-Cognitive Skills: Rotter Locus of Control (Std.)						-0.008**	-0.002
						(0.003)	(0.003)
Sample	Full	Sibling	Sibling	Sibling	Sibling	Sibling	Sibling
Demographics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Parental SES	No	No	Yes	Yes	Yes	Yes	Yes
Yearly FE	Yes	Yes	Yes	No	No	No	No
Sibling-Year FE	No	No	No	Yes	Yes	Yes	Yes
N	75,646	36,469	36,469	36,469	36,469	36,469	36,469
n	-	1,070	1,070	1,070	1,070	1,070	1,070
adj. R^2	0.05	0.07	0.12	0.21	0.22	0.21	0.22

Notes. All columns report linear regression estimates of the relationship between poor child health and adult risky asset market participation. Each column uses either a different sample or set of controls. In particular, column (1) uses the full sample and controls for demographics and yearly fixed effects. Column (2) reruns the specification from column (1) on the sibling sample. In column (3) and (4) we add controls for parental SES and replace yearly fixed effects by yearly sibling fixed effects, respectively. Columns (5) to (7) add, one-by-one and altogether, cognitive and non-cognitive skills to the regression specification. N denotes respondent-year observations and n refers to how many sibling-year units offer child health status variation. Standard errors are clustered at the sibling-year level.* p<0.1, ** p<0.05, *** p<0.01

negative and very similar significant estimate of the child health coefficient (-6.4 pp); additionally the model fit increases by 2 pp, which is in line with lower heterogeneity among siblings.

5.3.1. Parental SES, family background and skills

Addressing unobserved heterogeneity at the family level, we next add controls for fraternal and maternal education, fraternal occupation at age 14, net family income in 1978 and region at interview date in 1979. Column 3 of Table 3 shows that parental SES lowers the coefficient estimate of poor child health from -6.4 to -3.9 pp (-39%). Our estimate remains significantly different from zero at the 1% level and adding parental SES increases the model fit (adjusted R-Squared) from 0.07 to 0.12. Coefficient estimates of these family background controls are well-behaved as the stockholding likelihood increases in family income, maternal and fraternal education and white-collar occupation.

In column 4 we include yearly sibling fixed effects. Our model now explains 21% of the variation in risky asset market participation which is comparable to the Swedish yearly twin fixed effects regression of Calvet and Sodini (2014). However, perhaps unexpectedly, our coefficient estimate of interest increases slightly to -4.1 pp. Interestingly, Smith (2009a) finds the same pattern regarding a very similar child health proxy after including sibling fixed effects. A potential explanation argues that child health scales differ between respondents and thresholds are more similar among siblings. Differences in our health proxy are thus closer to true health disparities within families. As soon as we include yearly sibling fixed effects, we remove the family component of the reporting threshold, which should lead to larger health differences (Smith, 2009a).

Columns 5, 6 and 7 extend our yearly sibling fixed effects specification by cognitive, non-cognitive and both skills. According to theory, we would expect skills heterogeneity to explain most of the correlation. In fact, Table 3 reports that cognitive skills explain 44% of the remaining correlation. Our child health estimate stays significantly different from zero at the 5% level and our model fit increases by 1 pp. In line with the literature, the estimated relationship between AFQT score and participation decision is positive and significant (e.g. Grinblatt et al., 2011; Christelis et al., 2010). In particular, if we increase the AFQT score by one standard deviation, the likelihood to hold any risky asset increases by 8.7 pp.

Our measures of non-cognitive skills explain roughly 17% of the correlation among siblings (yearly) purged by family background and demographics. In line with the literature, we find non-cognitive skills to determine financial behavior (Hong et al., 2004; Luik and Steinhardt, 2016). According to column 6, an increase of one standard deviation in our standardized self-esteem and locus of control scores results in a significant 1.9 pp increase and 0.8 pp decrease in the likelihood to own risky assets. Therefore, self-esteem and an internal locus of control drive stockholding.

Adding both skills at once (column 7) explains about 53% of the correlation (column 4). The final coefficient for the poor child health-financial behavior correlation is -2 pp and remains significantly different from zero at the 10% level. Among siblings the true association seems to therefore lie between the lower and upper bound of -2 and -4.1 pp.[16] Including both skills at once and comparing their coefficient estimates indicate to what extent both skills capture the same required latent ability. While the decrease on cognitive test scores is modest (8.4 pp), its non-cognitive counterparts are reduced substantially. In particular, an increase in self-esteem increases the likelihood to participate by a significant 1 pp, whereas the coefficient on external locus of control approaches zero and turns insignificant at the 10% level. This is in line with the small improvement of the model fit.

Our results suggest that the correlation between poor child health and adult risky asset market participation can be particularly well explained by differences in cognitive skills and to a lesser extent by non-cognitive skills. While an unexplained part remains, more than half of the associaton can be attributed to characteristics recorded prior to labor market entry.

5.3.2. Alternative Explanations: Education, Health, Household Income and Economic Preferences

In the following, we offer different non-skill explanations for the remaining unexplained part of our negative association among siblings. These include education, economic preferences and adult SES, such as health and total household labor income. For each explanation we point out the relationship with adult portfolio choice, child health and skills.

Our first explanation is education (attained grade by 1996). Firstly, it is a key determinant of financial behavior (Campell, 2006); education allows increased asset ownership and accumulation via higher labor and subsequent capital income. In order to enter these higher income trajectories, education signals unobservable skills to employers. However, according to Cole et al. (2014), this is not the only channel at play. Regarding financial behavior, education increases awareness via courses with financial curriculum or

[16] The difference between lower and upper bound is the addition of controls for (non)cognitive skills which partially confound and mediate our effect. The displayed bandwidth is conservative in the sense that we control for yearly sibling fixed effects, and demographics.

lower costs of cognitive processing. According to child health, there is compelling evidence on a positive association between health status and educational attainment (e.g Case et al., 2005). Finally, education interacts with our underlying set of skills; for instance, while cognitive and non-cognitive skills certainly drive schooling success (Heckman and Rubinstein, 2001), school attendance could also be beneficial for the formation of non-cognitive skills. Therefore, while we expect education to capture much of the same underlying heterogeneity than skills, it should also explain its distinct share.

An alternative explanation is adult health, as poor health can affect financial behavior in various ways. Maybe the most intuitive explanation is it being a non-diversifiable background risk in the form of medical expenditure risk (Rosen and Wu, 2004). Households with poor health should therefore tilt their portfolio towards safer assets. According to Edwards (2008), however, the relationship could also run via the impact on the marginal utility of consumption or lifespan uncertainty affecting financial planning. Although the relationship could, in theory, go either way, the overall empirical evidence indicates a negative, yet not always significant, association between poor health and financial risk-taking (Love and Smith, 2010). Beyond affecting portfolio choice directly, health might also play a role via its dual positive relationship with adult SES measures (Smith, 1999). Regarding child health, there is also empirical evidence in favor of strong correlations between pre-/post-natal and later adult health status (Barker, 1990; Case et al., 2005). As shown in a recent study, besides deteriorating health capacity, health behavior is an important driver of this relationship as well (Kesternich et al., 2015). Considering the interaction with skills it is noteworthy that skill formation finished several years before our measurement of adult health (1988-2012). Nonetheless, there is empirical evidence in favor of non-cognitive skills driving risky health habits (Heckman et al., 2006; Cobb-Clark et al., 2014).

Our third explanation is total household labor income.[17] While it is crucial to pay risky asset market participation costs and accumulate wealth, the present value of discounted future income streams is also at the core of portfolio choice theory. Empirical evidence confirms the importance of income, income risk and human wealth for financial behavior in a number of studies (e.g. Calvet and Sodini, 2014). There is also considerable evidence on correlations between child health and individual labor market outcomes (e.g. Lundborg et al., 2014). According to Smith (2009a) poor child health affects total household labor income not only via individual earnings and labor supply but also via assortative mating and spousal labor market

[17] We construct this measure in line with Angerer and Lam (2009). Essentially we aggregate labor- and welfare income streams for singles and married couples.

characteristics. Considering the relationship with skills adult measured total household labor income takes place at least seven years after skills test-taking. Although Heckman et al. (2006) showed that cognitive and non-cognitive skills are strong predictors of adult labor market success, to the best of our knowledge there is no documented impact from adult income on skills, .

Finally, economic preferences might explain the remaining correlation.[18] Risk and time preferences are central to traditional portfolio theory. In particular, higher risk aversion and heavier future discounting both decrease the optimal risky share of financial wealth and participation likelihood. Research also suggests that risk and time preferences are related to health behavior (e.g. Courtemanche et al., 2015) and adverse traumatic childhood experiences, such as war (e.g. Kim and Lee, 2014). Becker et al. (2012) point out that economic preferences and non-cognitive skills are attempts to explain heterogeneity in individual behavior made by economists and personality psychologists, respectively. It is therefore reassuring that, despite their potential overlap, they only find a low association between both constructs; moreover, both constructs explain important SES outcomes in a complementary manner (Becker et al., 2012).

In order to assess the extent to which these alternative explanations explain our observed correlation, we extend our final specification with yearly sibling fixed effects in Table 4. However, as information on these suggested explanations is incomplete in our benchmark sample, we rerun our benchmark regression with and without skills on a smaller subsample with complete information in columns one and two. We then include education, health, total household labor income and economic preferences one-by-one (columns 3-6) and altogether (column 7).

Columns 1 and 2 suggest that our benchmark findings also hold in this subset of siblings. In particular, we obtain a larger negative and significant coefficient estimate for poor child health of -5.3 pp. Again, the coefficient decreases substantially (38%) after the inclusion of cognitive and non-cognitive skills.

Education explains another 11% of the benchmark correlation (column 3). In line with the empirical household finance literature, the estimated education coefficients increase in attained grade (e.g. Cole et al., 2014). Conditional on skills, the adult measures of health (column 4) and total household labor income

[18] In particular, we capture risk preferences with a dummy indicating if the respondent reports a willingness to take risk above five on a scale from zero to ten in 2012 (see e.g. Dohmen et al., 2011). Time preferences are recorded in 2006 via a discount factor constructed in line with Courtemanche et al. (2015). The household respondent answers which future payment (one year) is equivalent to a current receipt of hypothetical 1000 US Dollars.

(column 5) explain another 11 and 4% of the correlation among siblings.[19] In line with the empirical literature our estimates suggest a negative (positive) significant correlation between work-limiting health (total household labor income) and risky asset market participation. Adding preferences for risk and time in column 6 does not change the association. As expected (e.g. Dohmen et al., 2011; Kimball et al., 2008), we obtain significant positive estimates for lower risk aversion and less heavy discounting. In regards to these factors' correlations with skills, only the inclusion of educational attainment lowers the participation elasticity of skills and, thus, overall this stability of the skill coefficients highlights the additional explanatory power of each factor.

All four groups of controls together (column 7) render the long-run relationship insignificant at the 10% level and explain an additional 19% of the remaining correlation. Skills and our alternative explanations are therefore able to explain 57%. The moderate decreases in skills and alternative controls estimates highlight their associations with each other (e.g. via SES (Smith, 1999)). Conclusively, our results suggest that mostly pre-labor market differences in skill formation and to a much lesser extent subsequent education, adult health and total household labor income explain the long reach.

5.3.3. Blinder-Oaxaca Decomposition

In the previous section we found that cognitive and non-cognitive skills explain most of the correlation between poor child health and adult risky asset market participation. Thus far our results rely on yearly sibling fixed effects, which account for unobserved shared factors betweens siblings. While this has obvious advantages in terms of unobserved heterogeneity, excluding yearly sibling fixed effects could prove beneficial for our analysis for two reasons: first, if we compare how much skills explain in both frameworks, similar results further strengthen the case for a "partial" causal effect via this channel. In contrast to this, if skills' contribution is far more pronounced excluding fixed effects the effect might mostly run via unobserved shared family factors. Second, in the abundance of yearly sibling fixed effects we can conduct a (less computationally demanding) Blinder-Oaxaca decomposition analysis (Blinder, 1973; Oaxaca, 1973). As this method is robust to the ordering of inclusion and allows group-varying coefficients, we can compute how much of the participation gap can be explained by differences in characteristics. While this method is well-known for studying gaps and discrimination in labor and population economics, its popularity in

[19] Our measure of total household labor income is inverse sine hyperbolic transformed. The inverse sine hyperbolic transformation captures non-linearities for positive and negative values. In fact, for values that are not very small this transformation is approximately equal to the natural logarithm.

Table 4: Correlation Between Child Health and Adult Financial Behavior: Education, Health, Household Income and Preferences

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Poor Child Health	-0.053***	-0.033**	-0.027*	-0.027*	-0.031**	-0.033**	-0.023
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Cognitive Skill: AFQT (Std.)		0.085***	0.062***	0.084***	0.080***	0.084***	0.059***
		(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Non-Cognitive Skill: Rosenberg Self-Esteem (Std.)		0.011***	0.009**	0.011***	0.009**	0.011***	0.007*
		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Non-Cognitive Skill: Rotter Locus of Control (Std.)		-0.003	-0.003	-0.003	-0.003	-0.003	-0.003
		(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Education: 12y			0.002				-0.004
			(0.008)				(0.008)
Education: 13-15y			0.042***				0.032***
			(0.011)				(0.011)
Education: 16+			0.127***				0.110***
			(0.016)				(0.016)
Health Limitation				-0.039***			-0.020*
				(0.010)			(0.011)
$sinh^{-1}$ Total HH Labor Income					0.014***		0.012***
					(0.001)		(0.001)
Risk-Taker						0.026***	0.023***
						(0.007)	(0.007)
Discount Factor						0.032***	0.026**
						(0.012)	(0.012)
Sample	Sibling	Sibling	Sibling	Sibling	Sibling	Sibling	Sibling
Demographics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Parental SES	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Yearly FE	No	No	No	No	No	No	No
Sibling-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	32,569	32,569	32,569	32,569	32,569	32,569	32,569
n	782	782	782	782	782	782	782
adj. R^2	0.18	0.20	0.21	0.20	0.21	0.20	0.21

Notes. All columns report linear regression estimates of the relationship between poor child health and adult risky asset market participation. Each column includes yearly sibling fixed effects and controls for parental SES and demographics. Column (1) reruns the specification without skills on our new subsample of full information. Column (2) includes controls for (non)cognitive skills and columns (3) - (7) add one-by-one and altogether educational attainment, adult health limitations, total household labor income and economic preferences for risk and time, respectively. N denotes respondent-year observations and n refers to how many sibling-year units offer child health status variation. Standard errors are clustered at the sibling-year level.* p<0.1, ** p<0.05, *** p<0.01.

household finance has risen over the last years. For instance, Grinblatt et al. (2011) used decomposition analysis to explain the relationship between IQ and stock market participation. In a recent application, Luik and Steinhardt (2016) decompose the stockholding gap between native and immigrant U.S. households.

We run separate regressions for individuals with (group A) and without (group B) poor child health, whilst excluding the related indicator variable. The difference between predicted group risky asset holdings, Y_A and Y_B, can be decomposed into characteristics ΔX and coefficient effects $\Delta\beta$. Due to their observational nature, characteristics effects are also called the "explained gap", while coefficients effects are referred to as the "unexplained gap". The decomposition makes use of the group-specific independent characteristics X_A and X_B and regression coefficient estimates β_A and β_B. In line with Yun (2004) the overbars represent respective sample averages.

$$\overline{Y}_A - \overline{Y}_B = \underbrace{(\overline{X_A} - \overline{X_B})\beta_A}_{\text{characteristics effect } \Delta X} + \underbrace{\overline{X_B}(\beta_A - \beta_B)}_{\text{coefficients effect } \Delta\beta} \tag{11}$$

Yun (2004) points out that the decomposition can be extended to the detailed level. Each gap contribution is calculated by weighing the aggregate explained and unexplained gap. The underlying weights $W^i_{\Delta X}$ and $W^i_{\Delta\beta}$ are derived from a first-order Taylor extension around the functional value at the mean characteristics. Equations (14) and (15) clarify that the sum of all contributions add up to the aggregate decomposition gap.

$$\overline{Y}_A - \overline{Y}_B = \sum_{i=1}^{K} W^i_{\Delta X}[(\overline{X_A} - \overline{X_B})\beta_A] + \sum_{i=1}^{K} W^i_{\Delta\beta}[\overline{X_B}(\beta_A - \beta_B)] \tag{12}$$

$$\sum_{i=1}^{K} W^i_{\Delta X} = \sum_{i=1}^{K} W^i_{\Delta\beta} = 1 \tag{13}$$

In order to not over- or undervalue any group, we obtain a non-discriminatory coefficient from a pooled regression, augmented by a group membership dummy variable (Jann, 2008). As we are interested in "explaining" factors we do not have to tackle the issue of omitted categories highlighted for the detailed decomposition of the unexplained gap by Oaxaca and Ransom (1999).

As this decomposition has initially been developed for cross-sectional settings, we need to account for the different timing of our alternative explanations. For instance, large shares of the full impact of adolescent skills or education could be attributed to total household labor income. In Table 5, we therefore show decomposition results for different sets of controls. In particular, we extend controls step-wise; this allows us to attribute the full extent of explanatory power to early-life variables, such as parental SES, skills and alternative explanations taking place in middle adulthood. In column one, we start by controlling for demographics, parental SES and yearly fixed effects, while in column two we introduce our cognitive and non-cognitive skills. Thereafter we increase our set of controls by education (column 3), adult health (column 4), total household labor income (column 5) and economic preferences (column 6).[20] Coefficients are subsumed into "Demographics", "Parental SES", "Skills", "Education", "Health", "Income" and "Economic Preferences". Finally, we summarize yearly fixed effects in the "Wave" group.

The top of Table 5 reports predicted average risky asset market participation rates, the related gap and how much of it can be explained by differences in either characteristics or coefficients (including the constant). The predicted holding rates and gap are very close to our descriptive results in Table 2. In particular, we decompose a stockholding difference of 10 pp between respondents of poor (10 pp) and good (20 pp) child health. Column 1 indicates that differences in demographics, parental SES and yearly fixed effects explain roughly 63% of the entire holding gap. The complementary unexplained gap is significant at the 1% level. Adding skills to the decomposition in column 2 increases the explained gap to 9.1 pp, while the unexplained gap is rendered not significant and close to zero (-0.009); hence, cognitive and non-cognitive skills explain a distinct part of the correlation and together with family background and demographics almost the entire participation differential. Adding covariates for education, health, income and economic preferences in columns 3 to 6 closes the remaining narrow gap.

A detailed decomposition of each specification is presented in the bottom part of Table 5. Column 1 indicates that parental SES is the main driver of the explained gap in line with column 3 of our benchmark regression analysis in Table 3. However, roughly 37% of the gap remain unexplained. In column 2 almost

[20]For the ease of interpretation and computation, in contrast to the regression specification we replace quadratic age by birth year dummies. We thereby introduce increased flexibility, avoid pitfalls of lacking group variation in age dummies and still account for the age/cohort heterogeneity (birth year + age = year). Moreover, also due to insufficient group variation we drop individuals with missing information on region of interview in 1979. According to the NLSY79, these can include soldiers in oversea and individuals in U.S. territories.

Table 5: Blinder-Oaxaca Decomposition of the Risky Asset Market Participation Gap with Regards to Child Health

	(1)	(2)	(3)	(4)	(5)	(6)
Overall						
No Poor Child Health	0.200***	0.200***	0.200***	0.200***	0.200***	0.200***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Poor Child Health	0.100***	0.100***	0.100***	0.100***	0.100***	0.100***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Difference	0.100***	0.100***	0.100***	0.100***	0.100***	0.100***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Explained	0.063***	0.091***	0.092***	0.098***	0.100***	0.097***
	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Unexplained	0.037***	0.009	0.008	0.002	0.000	0.003
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Explained						
Demographics	0.016***	0.006***	0.011***	0.011***	0.010***	0.010***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Parental SES	0.048***	0.028***	0.021***	0.021***	0.021***	0.020***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Wave	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Skills		0.057***	0.037***	0.036***	0.034***	0.034***
		(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Education			0.023***	0.023***	0.021***	0.021***
			(0.002)	(0.002)	(0.002)	(0.002)
Health				0.007***	0.004***	0.004***
				(0.001)	(0.001)	(0.001)
Income					0.010***	0.010***
					(0.001)	(0.001)
Preferences						-0.001*
						(0.000)
Sample	Sibling	Sibling	Sibling	Sibling	Sibling	Sibling
Demographics	Yes	Yes	Yes	Yes	Yes	Yes
Parental SES	Yes	Yes	Yes	Yes	Yes	Yes
Yearly FE	Yes	Yes	Yes	Yes	Yes	Yes
Sibling-Year FE	No	No	No	No	No	No
N	32,174	32,174	32,174	32,174	32,174	32,174

Notes. All columns report linear Blinder-Oaxaca decompositions on the risky asset participation gap with regards to child health using the sibling sample with complete information. The upper and lower panel reports aggregate and detailed decomposition results following Yun (2004). Column (1) controls for demographics, parental SES and yearly fixed effects. Column (2) extends column (1) by (non)cognitive skills. Columns (3) to (7) sequentially add education, health, total household labor income and economic preferences, respectively. Standard errors are clustered at the household level.* p<0.1, ** p<0.05, *** p<0.01

the entire gap (91%) is explained with skills added. In this setting, skills contribute 57% and parental SES 28% to the explained gap. This indicates that skills capture sizable distinct heterogeneity. The decrease in parental SES and demographics suggests that much of their contributions could run through skill formation or an unobserved third variable, which is in line with Cunha and Heckman (2007)[21]. The remaining 10% of the gap can be explained by differences in education, health and adult labor income. Skills remain the single largest gap driver ranging from 34 to 57% of the explained gap in all columns.

As we find skills to be the main driver of the correlation with and without yearly sibling fixed effects, the correlation is less likely to be driven by unobserved family factors (Lundborg et al., 2014a). We can therefore argue in favor of a "partial" causal skills channel between early-life health and adult financial behavior.

5.4. Robustness Checks

In this section, we assess the robustness of our benchmark results. We, particularly, tackle two main potential caveats to our identification: differential parental treatment and functional form of estimation.

If unobserved differential treatment by parents is present, our results are likely to be biased. The direction of bias depends on parental preference for human capital inequality. For instance, if they compensate the child with poorer health with higher investments in their human capital, our estimate should be biased downwards. The same reasoning could apply for financial compensation. In Table 6, we test for the role of differential parental treatment by including either controls for birth order (columns 1 and 2) or (self-rated retrospective) parental affection (columns 3 and 4). Again, in order to assess the role of human capital, we reestimate our yearly sibling fixed effects framework with (columns 2 and 4) and without (columns 1 and 3) controls for skills.

Irrespective of controlling for differential parental treatment, the estimated gap is very close to our benchmark case (-3.8 and -4.2 pp). The same holds true for the change in the coefficient estimate before and after the inclusion of skills (-55%) . Our results thus indicate that there is no pronounced bias through differential parental treatment.[22]

[21] This assumes that child skills do not affect demographics and family SES.

[22] Also alternative explanations and decomposition analysis are robust to either inclusion. The results are available on request.

Table 6: Robustness Checks I: Parental Treatment (Yearly Sibling Fixed Effects)

	(1)	(2)	(3)	(4)
Poor Child Health	-0.042***	-0.020*	-0.038***	-0.017
	(0.011)	(0.011)	(0.011)	(0.011)
Cognitive Skills: AFQT (Std.)		0.084***		0.084***
		(0.005)		(0.005)
Non-Cognitive Skills: Rosenberg Self-Esteem (Std.)		0.010***		0.010***
		(0.003)		(0.003)
Non-Cognitive Skills: Rotter Locus of Control (Std.)		-0.002		-0.001
		(0.003)		(0.003)
Sample	Sibling	Sibling	Sibling	Sibling
Demographics	Yes	Yes	Yes	Yes
Parental SES	Yes	Yes	Yes	Yes
Yearly FE	No	No	No	No
Sibling-Year FE	Yes	Yes	Yes	Yes
Birth Order FE	Yes	Yes	No	No
Parental Affection	No	No	Yes	Yes
N	36,469	36,469	36,387	36,387
n	1,069	1,069	1,069	1,069
adj. R^2	0.21	0.22	0.21	0.22

Notes. All columns report linear regression estimates of the relationship between poor child health and adult risky asset market participation. Each column includes yearly sibling fixed effects and controls for parental SES and demographics. Columns (1) and (2) reruns the specification with birth order fixed effects, while columns (3) and (4) instead include controls for subjective retrospective parental affection in childhood. Only columns (2) and (4) control for (non)cognitive skills. N denotes respondent-year observations and n refers to how many sibling-year units offer child health status variation. Standard errors are clustered at the sibling-year level.* p<0.1, ** p<0.05, *** p<0.01.

While our LPM specifications are well-suited for sibling fixed effects frameworks (see applications in Smith, 2009a; Currie and Stabile, 2003; Oreopoulos et al., 2008) these models do not fully account for the non-linear relationship between covariates and a limited dependent variable. We therefore rerun our benchmark analysis using conditional (fixed effects) logit estimation (Table 7). We report estimates with and without skills controls. Yet again, we find a significant participation gap by child health status in both specifications. While conditional logit estimation does not allow us to calculate marginal effects, the reduction in coefficient estimate after the inclusion of skills is close to our benchmark results. Moreover, in results not reported here, the non-linear decomposition analysis obtains a very similar participation differential and attributes most of the gap to differences in cognitive and non-cognitive skills.[23]

6. Conclusion

Over the last decade research collected considerable empirical evidence on the long reach of poor child health. A well-established driving force of these long-run effects is the underlying gap in (human capital) skill formation, i.e. cognitive and non-cognitive skills (Cunha and Heckman, 2007). Assuming that child health affects adult outcomes via its impact on skill formation, there should exist associations between child health and any adult outcome that is also determined by human capital. However, despite human capital's importance for portfolio choice theory (Bodie et al., 1992) and financial behavior's key role for adult wealth accumulation, there is only very little ongoing research on related long-run relationships.

In this work, we test for a negative correlation between poor child health and adult risky asset market participation. Moreover, we test if differences in adolescent and young adult cognitive and non-cognitive skills can explain the majority of the long reach of child health. Using biological siblings of the NLSY79, our yearly sibling fixed effects regression results indicate a significant negative correlation between early-life health and risk asset market participation conditional on demographics and family background. Cognitive and, to a lesser degree, non-cognitive skills explain more than half of this within-correlation. Only part of the remaining association can be explained by education and factors of later lifecycle stages, including most notably adult health and total household labor income. Our results are confirmed by decomposition analysis excluding yearly sibling fixed effects which pronounces the role of skills even more and thus strengthens the case for child health affecting adult financial behavior via skills. Finally, our results are not driven by

[23] Also the inclusion of alternative explanations is robust to the estimation methodology. These and decomposition results are available on request.

Table 7: Robustness Checks II: Conditional Logit (Yearly Sibling Fixed Effects)

	(1)	(2)
Poor Child Health	-0.486***	-0.270*
	(0.143)	(0.150)
Cognitive Skills: AFQT (Std.)		0.668***
		(0.042)
Non-Cognitive Skills: Rosenberg Self-Esteem (Std.)		0.092***
		(0.028)
Non-Cognitive Skills: Rotter Locus of Control (Std.)		-0.019
		(0.028)
N	8,221	8,221
n	209	209
Log-Likelihood	-2,870.72	-2,707.82

Notes. All columns report conditional logit fixed effects estimates (yearly sibling fixed effects) of the relationship between poor child health and adult risky asset market participation. Each column also controls for parental SES and demographics. As indentification hinges on variation within yearly sibling units, the sample is substantially smaller. Only column (2) controls for (non)cognitive skills. N denotes respondent-year observations and n refers to how many sibling-year units offer child health status variation. Standard errors are clustered at the sibling-year level.* p<0.1, ** p<0.05, *** p<0.01.

differential parental investment or linear estimation specification.

This analysis has important policy implications. As risky asset market non-participation has adverse impacts on retirement preparation and future consumption, early-life health disadvantages can be carried further into the future. They thereby reduce welfare and increase capital inequalities for this and the next generation. Our results, accordingly, highlight the importance of good child health for a new adult SES outcome. Potential policy measures need to prevent children from poor health or assist poor families in the case of health shocks. Experimental evidence suggests that intervention programs in preschool targeting disadvantaged children can foster skill formation (Cunha and Heckman, 2007). Therefore these programs, such as Perry Preschool Program, might be fruitful remediations of poor child health in the context of adult financial behavior as well. Additionally, measures can include early-life exercise, nutrition programs and increased health insurance coverage.

References

Addoum, J. M., G. M. Korniotis, and A. Kumar (2015). Stature, obesity, and portfolio choice. *Management Science forthcoming*.

Agarwal, S. and B. Mazumder (2013). Cognitive abilities and household financial decision making. *American Economic Journal: Applied Economics 5*(1), 193–207.

Angerer, X. and P.-S. Lam (2009). Income risk and portfolio choice: An empirical study. *Journal of Finance 64*(2), 1037–1055.

Angrist, J. D. and A. B. Krueger (1999). Empirical strategies in labor economics. *Handbook of Labor Economics 3*, 1277–1366.

Barker, D. J. (1990). The fetal and infant origins of adult disease. *BMJ: British Medical Journal 301*(6761), 1111.

Barnea, A., H. Cronqvist, and S. Siegel (2010). Nature or nurture: What determines investor behavior? *Journal of Financial Economics 98*(3), 583–604.

Becker, A., T. Deckers, T. Dohmen, A. Falk, and F. Kosse (2012). The relationship between economic preferences and psychological personality measures. *Annual Review of Economics 4*, 453–478.

Becker, G. S. (1975). *Human capital: a theoretical and empirical analysis, with special reference to education* (1 ed.). New York: NBER Books.

Black, S. E., P. J. Devereux, P. Lundborg, and K. Majlesi (2015). On the origins of risk-taking. Technical report, NBER Working Paper No. 21332.

Blinder, A. S. (1973). Wage discrimination: Reduced form and structural estimates. *Journal of Human resources 8*(4), 436–455.

Bodie, Z., R. C. Merton, and W. F. Samuelson (1992). Labor supply flexibility and portfolio choice in a life cycle model. *Journal of Economic Dynamics and Control 16*(3), 427–449.

Calvet, L. E. and P. Sodini (2014). Twin picks: Disentangling the determinants of risk-taking in household portfolios. *The Journal of Finance 69*(2), 867–906.

Campell, J. Y. (2006). Household finance. *Journal of Finance 61*(4), 1553–1604.

Case, A., A. Fertig, and C. Paxson (2005). The lasting impact of childhood health and circumstance. *Journal of Health Economics 24*, 365–389.

Case, A., D. Lubotsky, and C. Paxson (2002). Economic status and health in childhood: The origins of the gradient. *American Economic Review 92*(5), 1308–1334.

Case, A. and C. Paxson (2008). Height, health, and cognitive function at older ages. *The American Economic Review 98(2)*, 463–467.

Cesarini, D., M. Johannesson, P. Lichtenstein, Ö. Sandewall, and B. Wallace (2010). Genetic variation in financial decision-making. *The Journal of Finance 65*(5), 1725–1754.

Chetty, R., J. N. Friedman, N. Hilger, E. Saez, D. W. Schanzenbach, and D. Yagan (2011). How does your kindergarten classroom affect your earnings? Evidence from Project Star. *The Quarterly Journal of Economics 126*(4), 1593–1660.

Chiteji, N. S. and F. P. Stafford (1999). Portfolio choices of parents and their children as young adults: Asset accumulation by African-American families. *The American Economic Review 89*(2), 377–380.

Christelis, D., T. Jappelli, and M. Padula (2010). Cognitive abilities and portfolio choice. *European Economic Review 54*(1), 18–38.

Christelis, D., D. L., and M. A. (2012). Early life conditions and financial risk-taking in older age. Technical report, ARC CEPAR Working Paper 2012/08.

Cobb-Clark, D. A., S. C. Kassenboehmer, and S. Schurer (2014). Healthy habits: The connection between diet, exercise, and locus of control. *Journal of Economic Behavior & Organization 98*, 1–28.

Cocco, J. F., F. J. Gomes, and P. J. Maenhout (2005). Consumption and portfolio choice over the life cycle. *Review of Financial Studies 18*(2), 491–533.

Cole, S., A. Paulson, and G. K. Shastry (2014). Smart money? The effect of education on financial outcomes. *Review of Financial Studies 27*(7), 2022–2051.

Courtemanche, C., G. Heutel, and P. McAlvanah (2015). Impatience, incentives and obesity. *The Economic Journal 125*(582), 1–31.

Cronqvist, H., A. Previtero, S. Siegel, and R. E. White (2016). The fetal origins hypothesis in finance: Prenatal environment, the gender gap, and investor behavior. *Review of Financial Studies 29*, 739–786.

Cunha, F. and J. Heckman (2007). The technology of skill formation. *American Economic Review 97*(2), 31–47.

Currie, J. (2009). Healthy, wealthy, and wise: Is there a causal relationship between child health and human capital development? *Journal of Economic Literature 47*(1), 87–122.

Currie, J. and D. Almond (2011). Human capital development before age five. *Handbook of Labor Economics 4*, 1315–1486.

Currie, J. and M. Stabile (2003). Socioeconomic status and child health: Why is the relationship stronger for older children? *The American Economic Review 93*(5), 1813–1823.

Dohmen, T., A. Falk, D. Huffman, U. Sunde, J. Schupp, and G. G. Wagner (2011). Individual risk attitudes: Measurement, determinants, and behavioral consequences. *Journal of the European Economic Association 9*(3), 522–550.

Fagereng, A., C. Gottlieb, and L. Guiso (2015). Asset market participation and portfolio choice over the life-cycle. *SAFE Working Paper Series*.

Fletcher, J. M. and S. F. Lehrer (2011). Genetic lotteries within families. *Journal of Health Economics 30*(4), 647–659.

Griliches, Z. (1979). Sibling models and data in economics: Beginnings of a survey. *The Journal of Political Economy*, S37–S64.

Grinblatt, M., M. Keloharju, and J. Linnainmaa (2011). IQ and stock market participation. *The Journal of Finance 66*(6), 2121–2164.

Haliassos, M. and C. C. Bertaut (1995). Why do so few hold stocks? *Economic Journal 105*(432), 110–1129.

Heckman, J., J. Stixrud, and U. J. (2006). The effects of cognitive and noncognitive abilities on labor market outcomes and social behavior. *Journal of Labor Economics 24*(2), 411–482.

Heckman, J. J. (2007). The economics, technology, and neuroscience of human capability formation. *Proceedings of the National Academy of Sciences 104*(33), 13250–13255.

Heckman, J. J. and Y. Rubinstein (2001). The importance of noncognitive skills: Lessons from the GED testing program. *The American Economic Review 91*(2), 145–149.

Hong, H., J. D. Kubik, and J. C. Stein (2004). Social interaction and stock market participation. *Journal of Finance 59*(1), 137–163.

Jann, B. (2008). The Blinder-Oaxaca decomposition for linear regression models. *The Stata Journal 8*(4), 453–479.

Keister, L. A. (2003). Sharing the wealth: The effect of siblings on adults wealth ownership. *Demography 40*(3), 521–542.

Kesternich, I., B. Siflinger, J. Smith, and J. Winter (2015). Individual behaviour as a pathway between early-life shocks and adult health: Evidence from hunger periods in post-war germany. *Economic Journal 125*(588), 372–393.

Kim, Y.-I. and J. Lee (2014). The long-run impact of a traumatic experience on risk aversion. *Journal of Economic Behavior & Organization 108*, 174–186.

Kimball, M. S., C. R. Sahm, and M. D. Shapiro (2008). Imputing risk tolerance from survey responses. *Journal of the American Statistical Association 103*(483), 1028–1038.

Kuhnen, C. M. and B. Melzer (2015). Non-cognitive abilities and loan delinquency: The role of self-efficacy in avoiding financial distress. *Working Paper*.

Love, D. and P. Smith (2010). Does health affect portfolio choice? *Health Economics 19*(12), 1441–1460.

Luik, M.-A. and M. Steinhardt (2016). Immigrant-native differences in stockholding - The role of cognitive and non-cognitive skills. *Journal of Empirical Finance 38(A)*, 103–119.

Lundborg, P., A. Nilsson, and D.-O. Rooth (2014). Adolescent health and adult labor market outcomes. *Journal of Health Economics 37*, 25–40.

Lundborg, P., P. Nystedt, and D.-O. Rooth (2014a). Body size, skills, and income: Evidence from 150,000 teenage siblings. *Demography 51*(5), 1573–1596.

Lundborg, P., P. Nystedt, and D.-O. Rooth (2014b). Height and earnings: The role of cognitive and noncognitive skills. *Journal of Human Resources 49*(1), 141–166.

Malmendier, U. and S. Nagel (2011). Depression babies: Do macroeconomic experiences affect risk taking? *Quarterly Journal of Economics 126*(1), 373–416.

Merton, R. (1969). Lifetime portfolio selection under uncertainty: The continuous-time case. *The Review of Economics and Statistics 51*(3), 247–57.

Oaxaca, R. (1973). Male-female wage differentials in urban labor markets. *International Economic Review 14*(3), 693–709.

Oaxaca, R. L. and M. R. Ransom (1999). Identification in detailed wage decompositions. *Review of Economics and Statistics 81*(1), 154–157.

Oreopoulos, P., M. Stabile, R. Walld, and L. L. Roos (2008). Short-, medium-, and long-term consequences of poor infant health an analysis using siblings and twins. *Journal of Human Resources 43*(1), 88–138.

Romeis, J. C., J. F. Scherrer, H. Xian, S. A. Eisen, K. Bucholz, A. C. Heath, J. Goldberg, M. J. Lyons, W. G. Henderson, and W. R. True (2000). Heritability of self-reported health. *Health Services Research 35*(5 Pt 1), 995.

Rosen, H. S. and S. Wu (2004). Portfolio choice and health status. *Journal of Financial Economics 72*(3), 457–484.

Samuelson, P. A. (1969). Lifetime portfolio selection by dynamic stochastic programming. *The Review of Economics and Statistics 51*(3), 239–246.

Smith, J. P. (1999). Healthy bodies and thick wallets: The dual relation between health and economic status. *Journal of Economic Perspectives 13*(2), 144–166.

Smith, J. P. (2009a). The impact of childhood health on adult labor market outcomes. *The Review of Economics and Statistics 91*(3), 478–489.

Smith, J. P. (2009b). Reconstructing childhood health histories. *Demography 46*(2), 38–403.

Vissing-Jorgensen, A. (2002). Towards an explanation of household portfolio choice heterogeneity: Nonfinancial income and participation cost structures. *NBER Working Paper No. 8884*.

Yun, M.-S. (2004). Decomposing differences in the first moment. *Economics Letters 82*(2), 275–280.

Table A.1: Description of Variables

Variable	**Description**	**Values**
Dependent Variable		
Risky Assets (>0)	Household owns a positive net value of stocks, funds, corporate/government non-US savings bonds	No = 0, Yes = 1
Child Health		
Poor Child Health	Respondent's self-reported childhood health has been fair or poor up to age 17	No = 0, Yes = 1
Demographics		
Age	Age at interview	Years
Male	Respondent is male	No = 0, Yes = 1
Nonwhite	Respondent is Black/African American or Hispanic	No = 0, Yes = 1
Parental SES		
Father Schooling (i)	Father of respondent attained i years of education, i= <12, 12, 13-15, 16+	No = 0, Yes = 1
Mother Schooling (i)	Mother of respondent attained i years of education, i= <12, 12, 13-15, 16+	No = 0, Yes = 1
Family Income in 1978 (i)	Total family income in 1978 is in tercile i of the family income distribution, i=1,2,3	No = 0, Yes = 1
Father White-Collar at Age 14	Father of respondent at age 14 works in a white-collar occupation	No = 0, Yes = 1
Region in 1979 (i)	Region at interview date in 1979 is i=North East (1), North Central (2), South (3), West (4)	No = 0, Yes = 1
Cognitive and Non-Cognitive Skills		
AFQT	Standardized respondent score of U.S. Armed Forces Qualification Test	Standard Normal Distribution
Self-Esteem	Standardized respondent score of Rosenberg's Self-Esteem test	Standard Normal Distribution
Locus of Control	Standardized respondent score of Rotter's (External) Locus of Control	Standard Normal Distribution
Alternative Channels		
Schooling (i)	Respondent attained i years of education by 1996, i= <12, 12, 13-15, 16+	No = 0, Yes = 1
Health Limitation	Respondent's health limits amount/type of work	No = 0, Yes = 1
Total Household Labor Income	$Sinh^{-1}$ of respondent's total family labor income	US-Dollar
Risk-Taker	Respondent's willingness to take risks in 2012 is larger than 5/10	No = 0, Yes = 1
Discount Factor	Respondent's discount factor in 2006	[0,1]
Year (i)	Interview Year i, i=1988, 1989,..., 2012	No = 0, Yes = 1

2016

173 Michael Berlemann; Marc-André Luik: Institutional Reform and Depositors' Portfolio Choice - Evidence from Bank Account Data, November 2016

172 Philipp, Lauenstein; Küster Simic, André: Information Processing in Freight and Freight Forward Markets: An Event Study on OPEC Announcements, September 2016

171 Nagel, Korbinian: A Life Course Perspective on the Income-to-Health Relationship: Macro-Empirical Evidence from Two Centuries, July 2016

170 Dluhosch, Barbara; Horgos, Daniel: International Competition Intensified - Job Satisfaction Sacrified?, June 2016

169 Beckmann, Klaus; Dewenter, Ralf; Thomas, Tobias: Can news draw blood? The impact of media coverage on the number and severity of terror attacks, May 2016

168 Afflatet, Nicolas: Deficit Policy within the Framework of the Stability and Growth Pact - Empirical Results and Lessons for the Fiscal Compact, April 2016

167 Werner, Max: Evaluating Prediction Markets for Internal Control Applications, May 2016

166 Werner, Max; Eißing, Klaus; Langton, Sebastian: Shared Value Potential of Transporting Cargo via Hyperloop, May 2016

165 Werner, Max; Vianelli, A.; Bodek, Mariusz C.: Monitoring Venture Capital Investments through Internal Control Prediction Markets, May 2016

164 Jahn, Vera; Steinhardt, Max Friedrich: Innovation and Immigration - Insights from a Placement Policy, February 2016

163 Beckmann, Klaus; Gattke, Susan; Lechner, Anja; Reimer, Lennart: Lineare dynamische Konfliktmodelle: Ein systematischer Überblick, Februar 2016

162 Beckmann, Klaus; Gattke, Susan; Lechner, Anja; Reimer, Lennart: A critique of the Richardson equations, January 2016

2015

161 Dewenter, Ralf; Schwalbe, Ulrich: Preisgarantien im Kraftstoffmarkt, Oktober 2015

160 Afflatet, Nicolas: Fiscal Policy in a Debt Crisis - A Model, June 2015

159 Beckmann, Klaus; Gattke, Susan; Reimer, Lennart: The Boulding-Richardson Model Revisited, June 2015

158 Jahn, Vera: The Importance of Mittelstand Firms for Regional Apprenticeship Activity - Lessons for Policy, April 2015

157 Im Winkel, Niklas: Rechts? Links? Liberal? Egal? Gründe für die Entstehung verzerrter Medieninhalte und Methoden zur Messung des Bias, February 2015

156 Afflatet, Nicolas: Public Debt and Borrowing. Are Governments Disciplined by Financial Markets?, January 2015

2014

155 Berlemann, Michael; Christmann, Robin: Determintants of In-Court Settlements. Empirical Evidence from a German Trial Court, December 2014

154 Berlemann, Michael; Christmann, Robin: Do Judges React to the Probabilty of Appellate Review? Empirical Evidence from Trial Court Procedures, December 2014

153 Bennöhr, Lars; Oestmann, Marco: Determinants of house price dynamics. What can we learn from search engine data?, October 2014

152 Dewenter, Ralf; Giessing, Leonie: The Effects of Elite Sports on Later Job Success, October 2014

151 Dewenter, Ralf; Rösch, Jürgen; Terschüren, Anna: Abgrenzung zweiseitiger Märkte am Beispiel von Internetsuchmaschinen, October 2014

150 Berlemann, Michael; Jahn, Vera: Governance, firm size and innovative capacity: regional empirical evidence for Germany, August 2014

149 Dewenter, Ralf; Rösch, Jürgen: Net neutrality and the incentives (not) to exclude competitors, July 2014

148 Kundt, Thorben: Applying "Benford's" law to the Crosswise Model: Findings from an online survey on tax evasion, July 2014

147 Beckmann, Klaus; Reimer, Lennart: Dynamiken in asymmetrischen Konflikten: eine Simulationsstudie, July 2014

146 Herzer, Dierk: Unions and income inequality: a heterogeneous panel cointegration and causality analysis, July 2014