Genetic Endowments and Wealth Inequality*

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ABSTRACT: We show that genetic endowments linked to educational attainment strongly and robustly predict wealth at retirement. The estimated relationship is not fully explained by flexibly controlling for education and labor income. We therefore investigate a host of additional mechanisms that could account for the gene-wealth gradient, including inheritances, mortality, risk preferences, portfolio decisions, beliefs about the probabilities of macroeconomic events, and planning horizons. We provide evidence that genetic endowments related to human capital accumulation are associated with wealth not only through educational attainment and labor income, but also through a facility with complex financial decision-making.

KEYWORDS: Wealth, Inequality, Portfolio Decisions, Beliefs, Education and Genetics.
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1 Introduction

Wealth inequality in the United States and many other countries is substantial and growing (Saez and Zucman, 2014; Jones, 2015). Income inequality explains only part of this phenomenon. After controlling for lifetime income, there remains significant heterogeneity in household wealth at retirement (Venti and Wise, 1998). Existing research attributes some of this variation to differences in fertility and other demographic choices (Scholz and Seshadri, 2007), differences in savings rates, and heterogeneity in the returns to wealth generated by different investment decisions (Benhabib, Bisin, and Zhu, 2011; Calvet, Campbell, and Sodini, 2007). Yet, the factors that produce differences in wealth accumulation are not fully understood. Learning more about these factors is important because policies are likely to have different effects depending on the origins of wealth inequality.

In this paper, we explore the relationship between genetic factors and household wealth. Our measure of genetic variation is a linear index of genetic markers, or *polygenic score*, associated with years of schooling. Polygenic scores have been constructed to predict a number of outcomes, and the score we use is specific to educational attainment. We demonstrate an economically large and statistically significant empirical relationship between the polygenic score and household wealth at retirement. We also document relationships between the score and a number of underlying factors relevant for wealth accumulation, including financial decisions and beliefs about the macroeconomy. Our results suggest that the genetic transmission of traits related to wealth may be one component of the intergenerational persistence of wealth (Charles and Hurst, 2003; De Nardi, 2004; Benhabib, Bisin, and Zhu, 2011; Black, Devereux, and Salvanes, 2005). They also suggest that an understanding of the intergenerational transmission of economic outcomes that does not account for the role of genetics is likely to be incomplete, possibly overstating the importance of other factors such as parental investments and financial transfers.

We begin by establishing a robust relationship between household wealth in retirement and the average polygenic score within the household. A one standard deviation increase in the score is associated with a 25 percent increase in household wealth (approximately \$165,347 at the median wealth, in 2010 dollars). The relationship between the polygenic score and wealth is present across time and education groups. Measures of educational attainment, including years of education and completed degrees, explain over two thirds of this relationship. Using detailed income data from the Social Security Administration (SSA) as well as self-reported labor earnings from the HRS, we find that labor income can explain less than half of the gene-wealth relationship that remains. After conditioning on lifetime income and household education, we find that a one standard deviation increase in the score is associated with a 5 percent increase in household wealth (approximately \$28,741 at the median).

Next, we explore additional mechanisms that may explain the gene-wealth gradient. Because individuals receive their genes from their parents, we first examine factors related to intergenerational transfers. We show that the polygenic score is positively related to parental education, which may proxy for transfers and advantageous family environments. We do not find a statistically significant relationship between higher scores and the probability of receiving an inheritance, nor with the size of the inheritance conditional on receiving one. The gene-wealth gradient remains economically large and statistically significant after controlling for both parental education and the size and incidence of inheritances.

We also consider savings behavior and portfolio choice as possible mechanisms through which genetic factors might operate. While the HRS is not well-suited for a direct analysis of savings rates, we examine whether previously documented determinants of savings are associated with the polygenic score. We find that higher individual polygenic scores predict lower objective probabilities of death as well as subjective beliefs about mortality, which may motivate higher savings rates in anticipation of longer lifespans.[1] We also document an as-

[1] This is related to the findings of Cronqvist and Siegel (2015), who use a twins design to study a genetic basis for savings behavior. However, they find that genes related to savings do not operate through genes related to education, but instead through time preference and self control because of genetic correlations between savings, smoking, and obesity.

sociation between an individual's polygenic score and measures of risk tolerance constructed from responses to hypothetical income and wealth gambles, which may affect both the savings rate and how savings are invested. This is consistent with previous research suggesting a genetic basis for risk preferences (Cesarini et al., 2009). We find strong evidence that households with different scores differ in *how* they save. In particular, we find that higher polygenic-score households are more likely to invest in the stock market, and this appears to play a particularly important role in mediating the relationship between the score and wealth.

Motivated by the findings on stock market participation, we next analyze aspects of financial decision-making that might give rise to differences in investment behavior. We show that lower polygenic scores are associated with beliefs about the probabilities of macroeconomic events that are less accurate relative to objective benchmarks. Lower scores are also associated with a greater propensity to believe that these events will occur with probabilities of 0 percent or 100 percent (a phenomenon we refer to as "extreme beliefs"). Large deviations between subjective and objective probabilities may reflect difficulty with probabilistic thinking. We also find that higher polygenic score households report longer planning horizons for financial decisions. This may indicate that these households are more patient, or that they are more comfortable with complex and abstract decision problems and therefore adopt longer planning horizons.

While we do not observe returns directly, our results provide a possible genetic microfoundation for the persistent differences in returns to wealth posited in a new wave of theoretical work. This line of research argues that cross-sectional heterogeneity in the returns to wealth is required to match the basic features of the wealth distribution (Benhabib, Bisin, and Zhu, 2011; Benhabib and Bisin, 2016). This argument is supported by a growing empirical literature that finds substantial heterogeneity in such returns (Fagereng et al., 2016; Benhabib, Bisin, and Luo, 2015; Bach, Thiemann, and Zucco, 2015). Much of this heterogeneity persists over time, with some individuals earning consistently higher returns to wealth (Fagereng et al., 2016). If the genetic gradient we study emerges from different returns to wealth brought on by differences in financial decision-making and beliefs about the macroeconomy, then relatively straightforward policy tools such as stronger public pension schemes may help to reduce wealth inequality stemming from genetic variation. This is especially relevant given the dramatic shift away from defined-benefit retirement plans towards options that give individuals greater financial autonomy (Poterba and Wise, 1998).

To explore this issue, our final set of results examines how the polygenic score interacts with a policy relevant variable: pensions. Because defined-benefit pensions offer recipients a guaranteed stream of income without requiring them to make choices about contribution rates or asset composition, such plans should reduce differences in wealth that arise from skill in financial decision-making. We find that the gene-wealth gradient is over four times as large for the subset of households who do not participate in defined-benefit pension plans. This exercise is useful for two reasons. First, it offers compelling support for the hypothesis that financial decisions may be a source of the gene-wealth gradient. Second, it also highlights a potentially important policy consideration. While more flexible plans like 401(k) accounts grant individuals greater freedom in planning for retirement, they may also reduce the welfare of those who find it more difficult to navigate complex financial choices.

This study relates to the literature on endowments, economic traits, and household wealth. One strand of this work examines how various measures of "ability," such as IQ or cognitive test scores, predict household wealth and similar outcomes (Grinblatt, Keloharju, and Linnainmaa, 2011; Grinblatt et al., 2015; Lillard and Willis, 2001).[2] However, parental investments and other environmental factors can directly affect test performance, making it difficult to use test scores to separate the effects of endowed traits from endogenous human capital investments. In contrast, genetic measures are *predetermined* if not exoge-

[2] As we discuss in greater detail in Section 2, when describing the genetic endowments examined in this paper we purposefully avoid the term "ability" because it is likely overly simplistic and imprecise. For example, the term does not emphasize multidimensionality of skill. The genetic endowments we study, which predict educational attainment, may capture some types of cognitive skill, but may also capture a host of other factors, such as personality or socio-emotional skills.

nous. That is, while polygenic scores are correlated with environmental factors, they are not directly manipulated by environments and investments in the same way as test scores.

A second strand of this literature focuses on genetic endowments, and seeks to estimate their collective importance using twin studies. Twin studies have shown that genes play a non-trivial role in explaining financial behavior such as savings and portfolio choices (Cronqvist and Siegel, 2014, 2015; Cesarini et al., 2010).[3] However, while twin studies can decompose the variance of an outcome into genetic and non-genetic contributions, they do not identify which particular markers influence economic outcomes.[4] This makes it more difficult to study the mechanisms through which genetic factors operate, or how they interact with environments. Moreover, it is typically impossible to apply twin methods to large and nationally representative longitudinal studies, such as the HRS, which offer some of the richest data on household wealth and related behavioral traits.

The remainder of this paper is organized as follows. Section 2 provides details on the genetic index used in this paper. Section 3 describes the data and provides details on key variables. Section 4 presents our main results on the relationship between the average household polygenic score and household wealth. Section 5 explores a host of possible mechanisms that can explain the gene-wealth gradient, including standard factors established in the literature along with measures of financial decision-making. Section 6 concludes.

[3]For example, using the Swedish Twin Registry, Cesarini et al. (2010) demonstrate that about 25% of individual variation in portfolio risk is attributable to genetic variation while Cronqvist and Siegel (2015) show that 35% of variation in the propensity to save has a genetic basis. It is worth mentioning, however, that these estimates may be biased upward if identical twins face more similar family environments than do non-identical twins (Fagereng et al., 2015).

[4]Variance decomposition exercises such as twins studies treat genes as unobserved factors. Testing hypotheses about specific mechanisms is conceptually possible using information on twins. In practice, learning about interactions between observed and unobserved factors is generally difficult and relies on modeling assumptions and requires large amounts of data to permit stratification by each potential mediating factor.

2 Molecular Genetic Data and Economic Analysis

Following recent developments in behavioral genetics, we investigate the relationship between genetic factors related to educational attainment and household wealth by using a linear index known as a polygenic score. In this section, we first provide details on the construction of the polygenic score, and then discuss what this approach can add to economic analysis. Our description of genetic data and related empirical techniques are intentionally informal; throughout this section, we provide citations for more rigorous and detailed treatments of this material. Moreover, we note that much of the background information presented here on the human genome follows Beauchamp et al. (2011) and Benjamin et al. (2012).

2.1 The Human Genome

DNA (deoxyribonucleic acid) molecules contain instructions that allow organisms to develop, grow, and function. The human genome consists of 23 pairs of DNA molecules called chromosomes, with an individual inheriting one copy of a chromosome from each parent. A DNA molecule is shaped like a double-helix ladder, where each "rung" is formed by one of two possible nucleotide pairs: adenine-thymine (AT), or a guanine-cytosine (GC). The genetic index that we study in this paper is constructed to measure variation in these nucleotide pairs. Since each location in the genome can feature one of two possible molecules, it is sometimes said that "the code of life is written in binary."

Across the entire human genome, there are approximately 3 billion locations featuring nucleotide base pair molecules. However, differences across people in these base pairs is observed at less than 1% of these locations.[5] Variation in the base pair molecules at a particular location is referred to as a single-nucleotide polymorphism (SNP, pronounced "snip"). Because individuals inherit two sets of chromosomes — one from each parent — at each SNP an individual can have either two AT's, two GC's, or one AT and one GC.

[5] Other forms of genetic variation exist. Such variation is typically referred to as structural variation and may include deletions, insertions, and copy-number variations (Feuk, Carson, and Scherer, 2006).

Genetic data thus most commonly take the form of a series of count variables indicating the number of copies of the reference molecule (AT's or GC's, depending on the location and conventions), possessed by an individual at each SNP: 0, 1, or 2. A central task in behavioral genetics involves determining which, if any, of these SNP variables are associated with behavioral outcomes.

2.2 GWAS and Polygenic Scores

Twins studies account for much of the existing literature on genetics and economic behaviors. A standard twins methodology estimates the fraction of the variance of a particular outcome attributable to genetic factors by comparing the outcomes of identical (monozygotic) twins and fraternal (dizygotic) twins. While identical twins share nearly all genetic markers in common, fraternal twins will share only about 50 percent of these markers. Twins studies often assume the following data generating process for an outcome of interest, Y_{if}, for individual i in family f:

$$Y_{if} = A_i + C_f + E_i. \tag{1}$$

Here A_i represents an additive genetic component, C_f represents common environmental factors affecting all individuals in family f, and E_i represents unique environmental factors affecting individual i. Differences in the covariance of Y_{if} between identical and fraternal twins allow one to identify the heritability of this outcome, which is the fraction of the variance of Y_{if} accounted for by genetic differences: $\frac{Var(A_i)}{Var(Y_{if})}$. Existing twins studies deliver heritability estimates of around 40% for education (Branigan, McCallum, and Freese, 2013).[6]

While twins studies provide an estimate of how much genetic factors collectively matter for explaining variation in a given trait, they do not reveal which specific SNPs are relevant. By contrast, Genome Wide Association Studies (GWAS) estimate associations between individual SNPs and outcomes of interest. A GWAS typically proceeds by gathering data

[6] Approaches that use adoptee studies provide similar but often lower estimates of heritability of education. See e.g., Sacerdote (2011) for a review.

on J observable SNPs, $\{SNP_{ij}\}_{j=1}^{J}$, and estimating J separate regressions similar to the following:

$$Y_i = \mu X_i' + \beta_j SNP_{ij} + \epsilon_{ij}, \tag{2}$$

where $SNP_{ij} \in \{0, 1, 2\}$ measures the number AT's or GC's (again depending on convention) possessed by individual i for SNP j, and X_i is a vector of control variables. Separate regressions for each SNP are estimated because in practice, one typically has many more genotyped SNPs than observations in a discovery sample.

The J individual regressions in a GWAS produce a set of coefficients $\left\{\widehat{\beta}_j\right\}_{j=1}^{J}$ — one for each SNP — with associated standard errors and p-values. Researchers interested in studying individual genetic markers typically focus on those SNPs exhibiting the strongest GWAS associations. Since traits like education are likely influenced by a large number of genetic markers, each with possibly small influences, the β_j estimated from (2) are often used to construct *polygenic scores* — indices formed by a linear combination of the GWAS coefficients. A polygenic score for a trait or outcome of interest is given by:

$$PGS_i = \sum_{j=1}^{J} \widetilde{\beta}_j SNP_i. \tag{3}$$

where the $\widetilde{\beta}_j$ in Equation (3) are versions of the $\widehat{\beta}_j$ coefficients estimated from Equation (2) that are adjusted to account for correlations between SNPs. There are many ways to perform this correction, and a detailed discussion of various methods is outside the scope of this paper. The polygenic score we use follows the Bayesian LDpred procedure of Vilhjalmsson (2015), which has been shown to perform better out of sample than other methods (Okbay et al., 2016), and we refer the reader to that study for details.

As shown in Equation (3), a polygenic score is simply a linear combination of SNPs and their effect sizes. While relatively few SNPs are likely to achieve *genome wide significance*[7]

[7]Given the large number of regression equations being estimated, correction for multiple hypothesis

— a stringent threshold for the statistical significance of a single β_j that accounts for multiple hypothesis testing and other factors — many polygenic scores include *all* SNPs included in the GWAS. In the case of educational attainment, previous studies have shown that a score using all SNPs produces better out-of-sample prediction than polygenic scores that use only genome wide significant SNPs (Okbay et al., 2016). In the context of Equation (1), the polygenic score can be thought of as the best SNP-based linear predictor of the common genetic component A_i.

2.3 The EA Score

GWAS have traditionally focused on medical or health-related outcomes, such as smoking (Bierut, 2010; Thorgeirsson et al., 2010) and obesity (Locke et al., 2015). However, the increasing availability of genetic data has made it possible to perform well-powered GWAS for behavioral traits with more distant relationships to underlying biological mechanisms. In particular, a series of landmark studies have delivered the first GWAS associations between individual SNPs and educational attainment, specifically years of schooling (Rietveld et al., 2013; Okbay et al., 2016; Lee et al., 2018). Existing work shows that polygenic scores for educational attainment based on these GWAS predict labor market outcomes, including earnings (Papageorge and Thom, 2018), and other measures of adult success (Belsky et al., 2016), even after controlling for completed education.

In this paper, we study a polygenic score based on the educational attainment GWAS results from Lee et al. (2018), which featured a discovery sample of over 1.1 million people.[8]

testing has been a key concern in this literature. For the purposes of determining whether an individual SNP-outcome association is statistically significant, the literature has adopted stringent p-value thresholds. A benchmark threshold for *genome wide significance* is $p < 5 \times 10^{-8}$. Stringent thresholds were developed in part as a response to earlier methods used to measure gene-outcome associations using so-called *candidate genes*, which are genes that the researcher believes may be implicated in an outcome arising from knowledge of biological processes. This approach suffered from false positives due to an uncorrected multiple-hypothesis testing problem (Benjamin et al., 2012).

[8]Specifically, the score is based on GWAS associations for 1,104,681 SNPs that pass the inclusion criteria documented in a set of technical notes provided in Okbay, Benjamin, and Visscher (2018). The score is constructed with the LDpred method, using parameters outlined in Okbay, Benjamin, and Visscher (2018).

Importantly, HRS data are not used to estimate the GWAS associations $\left\{\widehat{\beta}_j\right\}_{j=1}^{J}$ for this score, so every analysis in this study is an out-of-sample exercise.[9]

Prediction results from Lee et al. (2018) suggest that this score explains approximately 10.6 percent of the variation of years of schooling in the Health and Retirement Study. In what follows, we refer to this score as the Educational Attainment, or *EA score*.[10] It is reasonable to suspect that genetic endowments related to educational attainment may affect biological processes related to cognition that facilitate learning. Indeed, pathway analyses suggest that several of the SNPs most heavily tied to educational attainment are linked to biological processes known to be involved in brain development and cognitive processes (Lee et al., 2018; Okbay et al., 2016). Further, there is evidence of a high correlation between SNPs related to educational attainment and those associated with cognition (Okbay et al., 2016).[11] Results from Belsky et al. (2016) suggest that an earlier polygenic score for educational attainment predicts cognitive test scores for children in elementary school. However, it is important to note that the GWAS associations can reflect a range of traits — both cognitive and non-cognitive — that affect educational attainment through diverse mechanisms. We refrain from using the term "ability" when we refer to the EA score as it is likely too simplistic and may lead to the mischaracterization of the EA score as solely capturing cognitive function.

2.4 Interpretational Issues

Several caveats apply to the interpretation of variation in polygenic scores, and correlations between polygenic scores and outcomes. First, it is difficult to assign a causal interpretation to the estimated relationship between the score and outcomes. In particular, variation in the

[9]Details on genetic data used in this paper, along with instructions on how to obtain them, are found at the following URL: http://hrsonline.isr.umich.edu/index.php?p=shoavail&iyear=ZE.

[10]We maintain this nomenclature to distinguish this polygenic score from others that have been constructed to summarize genetic endowments related to different outcomes, such as depression, smoking, or subjective well-being.

[11]Bulik-Sullivan et al. (2015) consider a host of other related traits, but uses results from an earlier GWAS.

polygenic score may reflect differences in environments or parental investments rather than differences in genetic factors across individuals. Parents not only provide their children with genetic material, but also with the environments in which they are raised. It is therefore possible that higher polygenic scores could be associated with higher education and wealth largely through parental choices. We explore this point in greater detail when discussing our main findings.

Second, estimation error in the $\widehat{\beta}_j$ GWAS coefficients will generate measurement error in the polygenic score relative to a theoretical true genetic component A_i. In general, we expect this measurement error to attenuate the relationship between a polygenic score and an outcome.[12] As larger GWAS are conducted, the explanatory power of EA scores should in principle approach the theoretical upper bound, which is the heritability of educational attainment.

A third interpretational issue is related to functional form assumptions in the construction of polygenic scores. Polygenic scores like those in Equation 3 assume additively separable, linear relationships between SNPs and an outcome of interest. Of course, there may be nonlinearities and interactions between SNPs that would not be captured by this relationship. The presence of such departures from linearity may be one reason why polygenic scores tend to under-estimate the contribution of genetic factors relative to twins studies (Zuk et al., 2012).

Another concern is that associations between particular SNPs and an outcome of interest could reflect population stratification — that is, differences associated with characteristics of historical ancestry groups rather than biology at the individual level. For example, if a particular variant is more common in a specific ancestry group (e.g. Southern Europeans), then an observed association between this SNP and the outcome might reflect a combination of the biological function of the SNP and the common environment or social norms shared

[12]It is possible to use information about the heritability of education to provide an approximate correction for this kind of measurement error. If we assume measurement error is classical, doing this would increase the magnitude of the associations we estimate. Since this type of correction is valid only under strong assumptions about measurement error, we refrain from performing this exercise.

by this ancestry group. A common approach to control for such confounding effects is to include the first K principal components of the full matrix of SNP data in the GWAS control set X_i. In samples with ancestry differences, principal components have been shown to capture geographic variation, and therefore serve as controls for ancestral commonality (Price et al., 2006). Stated differently, the principal components help to control for ethnic background factors that would be absorbed by family fixed effects in research designs that exploit within-family variation. Unless otherwise noted, the first 10 principal components are always included in our empirical analyses.

A related concern is that GWAS results tend to best replicate in samples with a similar ancestral composition as the GWAS discovery sample. For this reason, we only consider individuals of genetic European ancestry as categorized by the HRS.[13] The score that we study was constructed using results from a sample of individuals of European ancestry, and previous work has shown that polygenic scores based on GWAS of genetic Europeans lack predictive power, and in some cases can generate bizarre predictions, when applied to non-European sub-samples. For example, applying a polygenic score for height discovered on a sample of individuals of European descent predicts very low average height relative to the observed distribution if applied to individuals of African descent (Martin et al., 2017).[14] It would thus be inappropriate to use this polygenic score for education to make predictions about individuals who are not of European descent.

[13]As part of the genetic data release, the HRS calculates polygenic scores and principal components that are specific to European ancestry groups. The HRS defines individuals of European ancestry as "... all self-reported non-Hispanic whites that had [principal component] loadings within ± one standard deviations of the mean for eigenvectors 1 and 2 in the [principal components] analysis of all unrelated study subjects." (Ware et al., 2018)

[14]The authors write, "the African populations sampled are genetically predicted to be considerably shorter than all Europeans and minimally taller than East Asians, which contradicts empirical observations (p. 7)"

3 The HRS Sample and Key Economic Variables

This section describes the definition of our analytic sample and the construction of key variables used in our analyses. We also address possible issues that arise from sample selection. Alternative samples and variables are discussed alongside the presentation of our main results in Section 4, although we note here that our main results are robust to a host of reasonable alternatives.

3.1 Sample Construction

The Health and Retirement Study (HRS) is a longitudinal study that follows Americans over age 50 and their partners. Surveys began in 1992 and occur every two years. The HRS collected genetic samples from just under 20,000 individuals over the course of four waves (2006, 2008, 2010, 2012). Our sample includes only those genotyped in the 2006 and 2008 waves, since the polygenic score we use has not yet been constructed for the 2010 and 2012 waves.

Our main analysis sample includes all households with at least one individual classified as a genetic European by the Health and Retirement Study. We drop households in which any member self-identifies as non-white. We further restrict our sample to include only retired households in years 1996, 1998, and 2002-2010.[15] We also include only those households with one or two members, and exclude households where both members are of the same sex because such households may have faced unique circumstances during their primary wealth-accumulation years. Finally, to minimize selection bias related to mortality, we include only household-year observations in which both members are between 65 and 75 years old. Our restriction aims to balance concerns about measurement error in wealth with concerns

[15] A household is categorized as "retired" if every member of the household is either not working for pay or reports that they are retired. This raises the possibility that some households are included in the sample because they are unemployed, even if they are not retired. This is unlikely to affect our sample given the age of the HRS respondents. The years 1992, 1994, and 2000 are excluded due to the incomparable measurement of components of wealth such as "dormant" retirement accounts — accounts that have accumulated benefits that reside with former employers.

about selection biases that arise if too many observations are excluded from the analysis. The resulting analytic sample includes 2,590 households and 5,701 household-year observations, with responses supplied for an average of 2.2 waves.

3.2 Education and Income

Table 1 provides summary statistics for key variables used in the main analyses. On average, the men in the sample were born two years before the women. While the mean years of education is similar for both men and women, the standard deviation is larger for men. Relatedly, men are more likely to have both high degree outcomes (College, MA, and Professional Degrees), and low degree outcomes (No Degree, GED).

Labor income is computed at the household level. Our primary source of earned income data comes from the *Respondent Cross-Year Summary Earnings* data set in the HRS. These data link individuals in the HRS to income data available through the Master Earnings File (MEF) maintained by the Social Security Administration (SSA). The MEF is constructed using data from employers' reports as well as Internal Revenue Service records including W-2 forms and other annual tax figures. The data include "regular wages and salaries, tips, self-employment income, and deferred compensation" (Olsen and Hudson, 2009).[16] The *Respondent Cross-Year Summary Earnings* provides annual MEF income totals for individuals over the period 1951-2013.

Our baseline income measure is the sum of all earned income in the MEF associated with a household for all available years through 2010, converted to 2010 dollars. This may include earnings from deceased spouses that are not directly observed in the HRS.[17] Table 1 summarizes the distribution of lifetime household income. The median household earned a

[16] Olsen and Hudson (2009) offer a detailed discussion of the evolution of the MEF, including the variety of records used to construct annual income in the file, as well as an account of how the kinds of income included in the MEF changed over time.

[17] For each year, we add observed earnings for an individual with any earnings reported for a deceased spouse in the *Deceased Spouse Cross-Year Summary Earnings* data set. After converting annual totals to real 2010 dollars, we then sum up all person-year income observations for each person in a household up through 2010.

total of $2.26 million. Lifetime income has a mean of just over $2.3 million with a standard deviation of just over $1.4 million.

One shortcoming of the SSA income data is that it is top-coded at the maximum taxable amount for Social Security payroll taxes. Table 1 shows that, on average, a household has over 12 years in which labor income is top-coded for at least one household member. As a partial solution, in cases where earnings are top-coded, we use Current Population Survey (CPS) data to impute the mean income for people earning at least the top-coded level in that year for the period 1961-2010 (Ruggles et al., 2018). In Section 4, along with our main results, we discuss the robustness of our results to alternative income measures, including self-reported HRS income variables that are not top-coded, but only record contemporaneous income.

3.3 Household Wealth

The HRS contains rich and detailed information on household wealth. Unfortunately, data related to household retirement wealth and stock market participation pose various challenges. Values of defined contribution plans from previous jobs are not asked in every wave; stock allocations in defined contribution plans are only asked in certain waves and only for plans associated with the current employer; and expected defined-benefit pension income is asked only of plans at the current employer. In some cases, such issues may be relatively unimportant. However, because this paper studies heterogeneity in wealth for elderly households, having a complete picture of retirement assets is of fundamental importance. While some data issues have no hope of being resolved, our sample comprises households for whom wealth data are most likely to be both accurate and comprehensive.

Our measure of *total wealth* is designed to encompass all components of household wealth. Our data include the present value of all pension, annuity, and social security income, which come from the RAND HRS income files, as well as the net value of housing (including primary and secondary residences as well as investment property), the net value of private businesses and vehicles, all financial assets including cash, checking accounts, savings accounts, CDs, stocks and stock mutual funds, bonds and bond mutual funds, trusts, and other financial assets, less the net value of non-housing debt. Each of these are taken from the RAND HRS wealth files.[18] Further, we include the account value of all defined contribution retirement plans.[19] We exclude the value of insurance policies from our wealth measure.[20] All monetary values are measured in 2010 dollars. Unless otherwise noted we winsorize the log of real total household wealth at the 1st and 99th percentiles.

We note that our measure of wealth includes both marketable securities, such as stocks which can be easily sold at publicly available prices, and non-marketable assets such as social security income. Our measure of wealth is therefore intended to capture the overall financial security of households rather than the market value of household assets. Our results are qualitatively unchanged if we limit household wealth to exclude retirement income and housing, which can be interpreted as the market value of households' pure financial assets.

Table 1 also contains summary statistics that describe the distribution of household wealth across all household-year observations in our sample. Although the median value of wealth is roughly \$593,640, the mean of \$900,170 (\$838,046 after winsorizing) indicates substantial skewness. Indeed, the 10th percentile of wealth is \$168,740, whereas wealth at the 90th percentile is \$1.7 million. The last three rows of Table 1 provide the median values of wealth after excluding housing and retirement accounts (defined contribution accounts as well as the present value of defined-benefit pensions and Social Security), separately, as well as their sum. The median value of wealth after excluding housing and pensions is approximately 15 percent of the baseline median. Additional details about the construction of the wealth and income measures, as well as summary statistics for the distribution of

[18]When calculating the present discounted value of annuity, social security, and defined-benefit pension income, we follow Yogo (2016) and assume a 1.5% guaranteed rate of return, discounted by the probability of death in each year conditional on age, cohort and gender of the financial respondent as determined by the Social Security life tables.

[19]Plans that are maintained either at previous employers for working households, or are still maintained by the previous employer for retired households, are referred to by the HRS as "dormant plans."

[20]Without further details on the structure or terms of specific insurance products it is difficult to estimate a market value for these items.

income, wealth, and other relevant variables are provided in Appendix A.

3.4 The EA Score in the HRS Sample

Since our unit of analysis is the household, we use the average EA score within households as our measure of genetic endowments. Hereafter, we use the term *EA score* to refer to the household average unless otherwise noted. Figure 1 plots the smoothed distribution of the EA score for our analytic sample. The score is normalized to have mean zero and variance of one, and is approximately normally distributed. Table 2 presents evidence of the raw relationships between the EA score and several key human capital measures and outcomes. Panel A of Table 2 presents the mean of education (years of schooling) and parental education, separately for men and women, by quartiles of the EA score distribution. Column [5] reports the difference between values in the first and fourth quartiles, while Column [6] reports the associated p-value. All three education measures are strongly and monotonically increasing in the EA score; women in the fourth quartile have nearly two more years of schooling than those in the first quartile, whereas men in the fourth quartile have nearly 2.4 more years than those in the first quartile. We again note that HRS data were not used in the construction of the score, so the relationship between the EA score and education documented in Table 2 constitutes an out-of-sample exercise. Similar patterns exist for parental education; individuals from households with higher EA scores tend to have parents with more education.

3.5 Sample Selection

We highlight two possible sources of selection bias in our sample: a) selection into genotyping, and b) selection based on retirement behavior and mortality outcomes. Appendix A provides summary statistics on differences between genotyped and non-genotyped HRS respondents. On average, genotyped individuals belong to older birth cohorts. Moreover, women and individuals with more education are more likely to agree to the collection of genetic data. Genotyped men, and individuals with lower levels of educational attainment may also be positively selected on unobserved factors that increase the likelihood of agreeing to the collection of biological data. If higher levels of education are associated with greater rates of participation, individuals with low EA scores who are genotyped may have higher than average values of other human capital traits. This form of selection bias could attenuate positive associations between the EA score and education or other related outcomes in our sample.

A second source of selection bias is linked to the criteria for inclusion in our sample. We limit our sample to retired households because defined benefit pension flows are important components of wealth for many households in the HRS, and they can only be measured for households that are retired and drawing these benefits. Including younger (non-retired) households would increase the size of our sample, but would introduce more measurement error in household wealth. However, restricting the sample to retired households may introduce selection bias if the EA score is associated with the timing of retirement.

In Table 3, we assess selection in our analytical sample by examining the relationship between the EA score and demographic characteristics that should be uncorrelated with the score in the absence of sample selection. Specifically, we divide individuals into quartiles based on their individual EA scores and report the fraction of males, average birth year, and average age for each quartile. Sex and birth year are measured cross-sectionally, while we include all person-year observations when calculating statistics for age. In Panel A we examine these patterns in our analytical sample, which includes all retired households with members aged 65-75. We indeed find selection on all three demographic variables. High EA individuals (fourth quartile) are 4.5% more likely to be male than low EA score individuals (first quartile). Because the SNPs used to construct the EA score are not found on sex chromosomes, the slightly higher representation of men in the fourth quartile of the EA score must result from selection. We also note that higher EA score individuals are more likely to belong to older birth cohorts, and are more likely to be observed at old ages. These age and cohort differences are likely to arise if individuals with higher EA scores live longer on average (which we explore in Section 5), and are therefore more likely to survive to be genotyped and less likely to die and exit the panel. While these differences are statistically significant, they appear to be modest in size. The average difference in birth year between the fourth and first quartiles is 1.2 years, while the average differences in age is 0.33 years.

The remaining panels of Table 3 display selection patterns for alternate samples. Panel B considers a sample of retired households with a wider range of ages (55-85). In this larger retired sample, there are substantially greater birth year and age differences between high and low EA score individuals compared to our analytical sample in Panel A. Panels C and D examine patterns among samples that include all households regardless of retirement status, for different age ranges (50-75 and $\leq$ 85, respectively). As one would expect, the samples that include all households feature smaller differences in these characteristics across EA score quartiles. However, the magnitudes of these differences are similar and relatively modest across alternate samples. Restricting our sample to retired households balances concerns about sample selection and measurement error.

4 The EA Score and Wealth

4.1 Main Association

Figure 2 provides visual evidence of the association between the EA score and wealth. The top panel of Figure 2 plots the unconditional, nonparametric (Lowess) relationship between the log of total household wealth and the average household EA score in our sample. The relationship between the EA score and wealth is increasing for normalized values of the EA score between -2 and 1 (over 80% of the sample), although it flattens and even declines somewhat after an EA score of 1. The size of the wealth differences are economically large; moving from an EA score of -1 to 1 implies a change in log wealth of approximately 0.48, or the equivalent of over $200,000.

The second panel of Figure 2 examines whether the relationship between the EA score and wealth holds within education groups. We plot the relationship separately for households in which at least one member has at least some college, and those in which all members have at most a high school degree. In both education subsamples, the relationship between the EA score and wealth is positive and substantial for EA scores between -2 and 1. For values of the EA score greater than 1 the relationship becomes flat (or even negative) for more educated households.

Panel B of Table 2 presents the (unconditional) mean of both total household income and household wealth for each EA score quartile. While total labor income is a cross-sectional measure with at most one observation per household, households may contribute multiple household-year observations for wealth. Panel B establishes our first main result: household wealth is strongly increasing in the EA score. A household in the fourth quartile of the household-average EA score has over $475,000 more wealth in retirement than those in the first quartile. The EA score also exhibits a large and statistically significant relationship with household income; households in the first quartile earned $2.13 million over their working lives compared to $2.51 million for those in the fourth quartile.

Figure 2 and Table 2 offer compelling evidence that the EA score and wealth are positively associated. We examine this relationship more formally in Table 4, which reports results from regressing log household wealth on the EA score for specifications with various sets of controls. Standard errors are clustered at the family level.[21] Column [1] shows the unconditional relationship between the EA score and the log of household wealth with no additional covariates. A one standard deviation increase in the EA score is associated with 24.6% greater wealth, and this result is highly statistically significant. In Column [2], we add basic controls for age (separately for males and females in each household), birth year

[21]Multiple households could be linked in our data if a once-married couple divorces or separates to become two distinct households. In such a case, the individuals in the divorced household would belong to three distinct households in our data, but just one family.

(separately for males and females), sex of the financial respondent, calendar time, and family structure.[22] Throughout the paper, these constitute our "standard controls." The inclusion of standard controls has only a modest effect on the coefficient on the EA score, which remains large and highly significant. In Column [3], we include the first 10 principal components of the genetic data and allow coefficients to vary for male and female household members.[23] These variables are intended to approximate family fixed-effects as explained in Section 2 (Benjamin et al., 2012). The principal components reduce the EA score coefficient from 0.221 to 0.218, and it remains statistically significant.

In Column [4] of Table 4 we add controls for years of schooling for each member of the household. Including years of schooling significantly reduces the size of the gene-wealth gradient, decreasing the coefficient to 0.085. This is unsurprising; the EA score was developed based on years of schooling, and education undoubtedly affects income and wealth accumulation over the life cycle. It is important to note, however, that the coefficient remains statistically and economically significant even after controlling for years of schooling. A coefficient of 0.085 suggests a one standard deviation increase in the genetic score is associated with approximately 8.5% greater wealth during retirement. In Column [5], we include more flexible measures of education. Instead of the simple count of years of schooling for each member, we include the following: a complete set of dummy variables for each year of schooling for the male household member, dummies for every highest completed degree for the male household member, interactions between all male education dummies and an

[22] We add the following: a set of dummies for every possible age for the male household member, interacted with an indicator for a male only household, a complete set of dummies for every possible age for the female household member, interacted with an indicator for female only households, complete sets of dummies for male and female birth years, also interacted with indicators for male only and female only households respectively, dummies for calendar year, an indicator for male financial respondent, and dummies for a male only household and female only household. We note that the age variables are constructed even for deceased household members. The appendix contains robustness exercises that explicitly control for the years since the death of a household member.

[23] We include the first 10 principal components for the male household respondent, along with interactions with a dummy for being in a male only household, the first 10 principal components for the female household, along with interactions with a dummy variable for being in a female only household, and separate dummies indicating missing genetic data for the male and female household members, respectively. The principal components for individuals who are not genotyped are set to zero.

indicator for male-only households, an identical set of dummies for the female household member, and a full set of interactions between the male and female years of schooling dummies and degree dummies. We refer to this set as "full education controls". Including the full set of education controls reduces the EA score coefficient to 0.070. Even in this specification the coefficient remains highly statistically significant.

In Column [6], we include the standard controls and principle components and add controls for labor income. In particular, we include the total of lifetime earnings for the household from the SSA data described in Section 3. Controlling for income reduces the coefficient on the EA score from 0.218 to 0.179, which remains statistically significant. In Column [7], we add the full set of education variables along with income and other controls. The results are consistent with Columns [5] and [6]. The coefficient on the EA score is 0.047, (p-value = 0.03), suggesting that a one standard deviation increase in the EA score is associated with 4.7% greater wealth.

Table 4 indicates that the EA score is associated with wealth even after controlling flexibly for completed schooling and degree type. One interpretation of this result is that the score measures genetic traits that promote wealth independently of any effects on the acquisition of human capital. However, it could also be that the education variables in the HRS are measured with error, or do not fully reflect the educational investments associated with genetic factors. If so, then the remaining genetic gradient in Column [7] may simply result from the effects of unobserved human capital investments rather than genetic factors. In particular, our control set does not include measures of school quality, which has been studied as a potentially important dimension of educational investment (Behrman and Birdsall, 1983).[24]

Given results linking higher quality teachers to higher adult earnings (Chetty, Friedman,

[24]Recent evidence on school quality is mixed. Some papers show evidence that charter schools and schools with more funding improve outcomes on test scores and post-secondary educational outcomes (Deming et al., 2014; Jackson, Johnson, and Persico, 2015; Angrist et al., 2016) and reducing racial achievement gaps (Dobbie and Fryer Jr, 2011). Other work shows that the impact of higher school quality is very small once selection into more prestigious schools is accounted for (Abdulkadiroğlu, Angrist, and Pathak, 2014). See Card and Krueger (1996) for a survey of earlier literature on school quality effects.

and Rockoff, 2014), observed lifetime earnings may contain information about the quality of schools that an individual attended. Since controlling for lifetime earnings attenuates the relationship between the EA score and wealth, higher values of the polygenic score may be associated with access to better quality schooling. However, controlling for lifetime income causes the coefficient on the polygenic score to shrink by at most one third, leaving a substantial unexplained gradient. Nonetheless, measurement error in income is still a concern. It may be that complete measures of income that do not suffer from top-coding or reporting biases fully account for the gene-wealth gradient once education (even improperly measured) is included. While we assess the robustness of our results to various income specifications below, the reader should interpret our results with these potential measurement issues in mind.

4.2 Robustness

Figure 2 and Table 4 show a strong, economically large relationship between the average household EA score and household wealth. In Table 5, we provide results from alternative specifications that address three potentially important choices in the formation of our main sample: the use of the average household EA score, the restriction to retired households, and the use of income data from the SSA. For each, we repeat the specifications in Columns [5] and [7] from Table 4.

Our measure of genetic endowments is the household average EA score. Averages can mask important differences across households depending on the degree of assortative mating and the structure of intra-household decision-making. In Appendix B, we find modest evidence of assortative mating; couples' EA scores are correlated with a coefficient of $\rho = 0.137$, although we cannot reject random matching once we condition on education.

If EA scores are not highly correlated across individuals within a household, this raises the question of whose score matters. The intra-household division of tasks and financial decision-making may have a meaningful effect on our results. A reasonable hypothesis is that an individual's EA score should matter more if they assume more financial responsibility within the household. In Columns [1] and [2] of Table 5, we replace the average household EA score with separate individual scores for the financial respondent (FR), who answers financial questions on behalf of the household, and non-financial respondent (NFR). The average individual EA score for the FR is 0.09, while it is -0.04 for the NFR, suggesting modest differences between the EA scores of the FR and NFR. If, for example, the FR has sole responsibility for the financial decisions of the household, the FR's EA score may have a larger association with wealth than the household average score. Alternatively, complementarities would imply that conditional on the FR's EA score, a higher EA score of the NFR could also associate with greater wealth.[25] Columns [1] and [2] show that the FR score is more predictive than the NFR's score. While the coefficient on the NFR score remains positive even conditioning on the FR score (0.023 and 0.019 for the two specifications, respectively), it is statistically indistinguishable from zero at conventional levels. In other words, once we condition on household income and both spouses' education along with the FR score, the NFR score no longer predicts household wealth.

In Columns [3] and [4] of Table 5, we relax the retirement requirement and include both retired and non-retired households. For non-retired households with defined-benefit pensions, economic resources are understated since we do not include expectations of future defined-benefit income. Compared to individuals in our main analytic sample, this sample includes individuals that are younger, more highly educated (by at least a third of a year of schooling for both men and women) and exhibit higher lifetime income ($2.4 million versus $2.3 million for our baseline sample). The coefficients on the EA score in columns [3] and [4] are 0.079 and 0.057, similar to our main results in Table 4, and remain highly statistically significant. This suggests our restriction to retired households is not an important factor driving the relationship between the EA score and wealth. Nonetheless, we maintain the retirement restriction for our main sample to ensure completeness of the wealth data and to

[25]This could occur if partners exchange information, a point made in Benham (1974) who studies the benefits of women's education for the household.

facilitate our analysis of the gene-wealth gradient within defined-benefit pension participation in Section 5.

Finally, in Columns [5] and [6], we consider the log of the household's average self-reported labor income in the HRS as an additional control.[26] For this specification, we necessarily restrict the sample to households that are ever observed in the HRS with at least one working member, since this is required to obtain an in-sample measure of total income. The self-reported income data in the HRS are not subject to top-coding like the SSA data. However, because the HRS is a sample of elderly Americans, this necessarily means that HRS labor income is observed toward the end of the life-cycle or not at all. These differences are meaningful. Average annual household income in our sample based on HRS data is $57,769 and the correlation coefficient between the log of this HRS average and the log of total income using SSA data is 0.32. Column [5] presents the coefficient on the EA score once we restrict the sample to households with non-missing HRS income. The results in Column [6] indicate that both the SSA and HRS income variables independently predict wealth. Nevertheless, the estimated coefficient on the EA score is 0.044 (p-val = 0.058) when both income measures are included — similar to the baseline estimates in Column [7] of Table 4.

In Appendix C we provide numerous robustness tests for the main association between the EA score and wealth documented in Table 4. Additional summary statistics, including those relevant for this section and later analyses, are included in Appendix A.2. In separate analyses, we test the importance of sample selection by using HRS sampling weights, using only one household-year per sample, and by restricting analyses to only "coupled" households — i.e., those where two members are observed for at least one household-year observation. We also examine robustness to alternate sample definitions with different age restrictions, as well as those that include non-retirees. Additional specifications control for more complicated

[26] Specifically, for each member of the household, we consider only years in which they are not retired and report working for pay. We add up real income for each household within a particular year, and average across available years in the HRS up through 2010.

functions of household income, including the number of years with top-coded income, and use alternate definitions of household wealth that exclude retirement and housing wealth. We also examine robustness to the use of different versions of the EA score, and to the inclusion of more extensive controls including cognitive ability, number of children, the death of a household member, and years since retirement. Generally, results in Table 4 are robust to these exercises.

4.3 Transfers and Parental Education

A likely candidate to explain the remaining portion of the gene-wealth gradient is parental transfers that are not captured by completed education or earned income. Individuals inherit their genetic material from their parents, and those parents shape childhood environments. Thus, differences in the EA score could reflect not only differences in genetic factors that promote educational attainment but also environmental factors that affect education and other outcomes regardless of one's genes. As evidence of this possibility, Lee et al. (2018) find that associations between SNPs and educational attainment tend to be smaller using only within-family variation as opposed to within and across family variation. Moreover, Kong et al. (2018) show that even those SNPs carried by parents that are *not* passed on to children are correlated with children's outcomes, presumably through parental environments. Indeed, one of the largest challenges in interpreting variation in the EA score comes from gene-environment correlations. An important limitation of our analyses is that we are not able to cleanly separate the association between the EA score and wealth into genetic and environmental components.

In Table 6, we examine the extent to which the transfer of resources from parents to children — either indirectly through more advantageous environments as proxied by parental education, or directly through monetary bequests — can explain the gene-wealth gradient.[27]

[27]In Appendix A, we provide additional summary statistics on these variables. We also show that after controlling for respondent education, the EA score is unrelated to the likelihood of receiving an inheritance or the size of the inheritance conditional on receiving one. Unsurprisingly, parental education is correlated

Roughly 40% of households report receiving an inheritance and among those who do, the average amount is approximately $160,617. Average fathers' and mothers' education for the household are 9.47 years and 9.95, respectively.

In Column [1] of Table 6, we provide a baseline specification that repeats Column [5] of Table 4 and includes the standard controls, principal components, and full education controls. In Column [2], we include an indicator for ever receiving an inheritance in the HRS data, and the log of total inheritances received by all members of the household while in the HRS. The log inheritance variable is set to zero for households that do not receive an inheritance. As expected, inheritances are highly correlated with household wealth. However, the inclusion of inheritances changes the coefficient on the EA score only marginally, from 0.070 to 0.064. Next, we include years of schooling for each parent of each member of the household, along with a set of dummy variables indicating missing values for these variables. The education of the father of the female member of the household appears to be related to wealth, but the inclusion of parental education as a control once again reduces the coefficient on the EA score only slightly. In Column [4], we include both parental education controls and the log of the sum of lifetime inheritances. The inclusion of the full set of proxies for parental investments reduces the coefficient on the EA score to 0.058, implying a one-standard deviation increase in the EA score increases total wealth by 5.8%, and remains statistically significant at the 5% level.

The results in Table 6 show that the remaining portion of the gene-wealth gradient does not fall substantially when we include additional parental background variables intended to capture direct and indirect transfers. It may be the case that parental investments are largely captured by respondents' completed education and labor income. These results suggest that the EA-score wealth correlation may in part be driven by additional mechanisms not examined in this section. We address potential alternative mechanisms in the following section.

with higher EA scores even after we control for respondents' education.

5 Additional Mechanisms

This section considers possible channels beyond income, education and parental transfers through which the EA score may relate to wealth. Specifically, we investigate risk aversion, mortality (which could affect savings), and investment decisions such as stock market participation, home ownership, and business ownership. We also consider how the EA score relates to different dimensions of financial decision-making, including beliefs about macroeconomic events and reported planning horizons. Finally, we show differences in the gene-wealth gradient depending on whether individuals receive income from defined-benefit pensions. A complete set of summary statistics for each potential mechanism are provided in Appendix A, but we provide means when analyzing each potential mechanism below. We also provide means for outcome variables in each corresponding table.

5.1 Mortality

One way in which wealth may be related to genetic endowments is through longevity, which has been shown to be correlated with genetic variants linked to education (Marioni et al., 2016). If individuals with higher individual EA scores expect to live longer, they may endogenously save more to finance these additional years of consumption. Furthermore, longer expected lives may lead to longer investment horizons, which may affect the mix of assets in household portfolios. We therefore examine whether the score is associated with realized and expected longevity in our sample. We forgo a direct analysis of savings rates because the HRS consumption and expenditure data are only available for a small sub-sample of households, which may leave tests to detect differences in savings rates underpowered. Further, given the age of the sample, the data do not include the prime working (and saving) years of the household, which are likely the most informative for such an analysis.[28]

[28] In results available from the authors, we show that the EA score is not related savings (as measured by consumption and expenditures as a portion of income). We do not present these results because of the data issues outlined above.

The one-year mortality rate in our sample (excluding years before genotyping) is 0.04. The average subjective probability of living to 75 years old, for individuals in our analytic sample is approximately 67 percent. We begin our analyses by directly estimating the empirical relationship between the individual's EA score and mortality. Since here we are studying individual mortality outcomes, we use the individual's own personal EA score as opposed to the household average score. We construct an indicator variable equal to one if the individual dies in the next year, and estimate a linear probability model of the likelihood of dying in a particular year as a function of the individual's EA score, the principal components, and dummy variables for age, birth year, years of schooling, and degree. We restrict this regression to person-years in which an individual was between the ages of 50 and 90, and we drop years before an individual was genotyped. Table 7 provides the results of this regression. In Column [1] we include both females and males in the sample, and find that a one standard deviation increase in the individual's EA score is associated with a 0.3 percentage point decline in the one-year mortality rate. Columns [2] and [3] consider females and males separately. The estimated association for females implies a 0.5 percentage point decline in the mortality rate for every one-standard deviation increase in the EA score. We find no relationship for males.

We also consider beliefs about mortality. In principle, objective mortality should only affect behavior if individuals expect to live longer. In this sense, beliefs about mortality are perhaps the more relevant mechanism linking genetic endowments to wealth. The HRS repeatedly asks individuals to provide their subjective beliefs for the probability that they will live to the age of 75. In Column [4], we regress this subjective belief on the individual EA score, our standard controls, and the full set of education controls in a sample of individuals aged 50-65. We do not find a significant association between the EA score and the level of this subjective probability. We also estimate this regression for females and males separately in Columns [5] and [6], and find that for females a one standard deviation rise in the individual's EA score predicts a 0.66 percentage point rise in reported beliefs about living to age 75.

For males, the relationship is negative and statistically insignificant. In total, we find a non-trivial relationship between the EA score and mortality rates, but no association with expected mortality. This may offer some evidence that part of the gene-wealth gradient arises from the prospect of greater longevity.

5.2 Risk Aversion

We next examine if the EA score is associated with differences in *how* households save. A well-established source of heterogeneity in household wealth is returns to risky endeavors, such as participation in risky asset markets or business ownership. One mechanism that may therefore relate the EA score to wealth is aversion to risk. To examine the relationship between risk aversion and the EA score, we use questions in the HRS designed to elicit measures of risk tolerance based on hypothetical income and wealth gambles. Generally, these questions pose hypothetical scenarios in which the respondent faces a choice between a guaranteed endowment of wealth or stream of income, or a 50-50 gamble that will result in a permanent increase or decrease in that endowment or income. Specifically, respondents are asked to choose between two jobs: "The first would guarantee your current total family income for life. The second is possibly better paying, but the income is also less certain. There is a 50-50 chance the second job would double your total lifetime income and a 50-50 chance that it would cut it by X." The series replaces X with a set of possible income losses: ten percent, twenty percent, one-third, one-half, or seventy five percent. Additionally, respondents are asked one of two hypothetical wealth gambles with a similar structure. One is based on an inherited business worth one million dollars today, or that may be sold in one month with a 50-50 chance of being worth two million dollars or X. The other is based on an immediate inheritance worth one million dollars, with the potential to participate in a risky business venture that has a 50-50 chance of doubling in value or falling in value by X. In each case, X varies by the same proportions as the hypothetical income gamble.

Based on the responses to these hypothetical gambles, each respondent can be grouped by the smallest downside for which they still reject the gamble. We create a dummy variable for each gamble that takes a value of one if an individual always responds with a preference for the guaranteed wealth or income. A value equal to one for this variable indicates the highest degree of risk aversion permitted with this set of questions. 39% of respondents comprise the most risk averse households, who would not take a 50-50 gamble that would double their income or cut it by 10%. Alternatively, only 5% of respondents would take a 50-50 gamble where the downside is a 75% reduction in income.

In Column [1] of Table 8, the dependent variable is our binary indicator for the highest degree of risk aversion based on the labor income gamble. We find a negative association between the average household EA score and risk aversion — a one standard deviation increase in the score is associated with a reduction in the probability of the most risk averse response by 2.2 percentage points. In Columns [2] and [3], we use indicators for greatest risk-aversion based on the inheritance and business risk questions as the dependent variables. We find no statistically significant relationship between the EA score and risk aversion for the inheritance question, but do find that the probability of a respondent giving the most risk averse response for the business risk question is 2.7 percentage points lower for a one standard deviation increase in the EA score, which is significant at the 0.05 level.

In Columns [4]-[6], we allow the outcome variable to be an ordered categorical variable indicating the riskiest gamble that a respondent accepts. This variables can take one of six values, with higher values corresponding to higher degrees of risk aversion. We estimate an ordered probit model in these specifications, and report coefficients for the latent index. Column [4] shows that the EA score is associated with a significant decrease in the latent index for risk aversion for income. Columns [5] and [6] repeat the ordered probit estimation for the inheritance and business wealth gambles, respectively. Again, we find no statistically significant relationship between the EA score and risk aversion based on the hypothetical inheritance wealth gambles, but do find a significant relationship with risk aversion for the business wealth gamble.

5.3 Stocks, Housing, and Business Ownership

Motivated by the relationship between the EA score and elicited measures of risk aversion, we examine whether the EA score is related to stock market participation, business ownership, and owning a home. Each of these asset classes is the subject of a well-established literature highlighting their importance as a source of heterogeneity in wealth accumulation over the life-cycle. Eighty-four percent of households own a house, while 8% own a business and 46% own stocks.

Panel A of Table 9 regresses indicator variables for stock market participation, business ownership, and home ownership on the average household EA score and our full set of standard controls, including education variables. Columns [1]-[3] also include the log of total lifetime household income from the SSA data as an additional control. In Column [1] we find no statistically significant relationship between home ownership and the EA score, but we do find a significant relationship between home ownership and lifetime earnings. In Column [2] of Panel A, we find no relationship between business ownership and the EA score, nor between business ownership and lifetime labor income. Column [3], however, shows a strong positive association between the EA score and stock market participation. A one standard deviation increase in the EA score is associated with a 5.2 percentage point increase in the probability of owning stocks, and this coefficient is statistically significant at the 1% level. Compared to an average rate of stock ownership of 46%, the coefficient suggests this predicted increase in participation is also economically meaningful.

Of course, stock market participation is likely affected by accumulated wealth, which has already been shown to strongly correlate with the EA score. This suggests that the relationships between the EA score and stock market participation may operate purely through wealth. This possibility is addressed in Columns [4]-[6], which repeat the specifications in Columns [1]-[3] but also include the log of financial wealth from the previous wave. Consistent with the existing literature, we find that the coefficient on lagged wealth is large and statistically significant for all three asset types. We continue to find no evidence of a relationship between the EA score and home or business ownership after controlling for lagged wealth. However, the relationship between the EA score and stock ownership remains significant and economically meaningful after controlling for lagged wealth. A one standard deviation increase in the EA score is associated with a 4 percentage point higher likelihood of owning stocks, with statistical significance at the 1% level. Because stocks have traditionally offered substantially higher returns than other liquid securities such as money-market funds or bonds, this may be an important factor for explaining the gene-wealth gradient, and may also suggest that these genetic endowments provide a microfoundation for the persistent differences in returns to wealth.

To examine the extent to which the important components of household saving — home, business, and stock ownership — can be possible explanations for the association between the EA score and wealth, we include each in regressions of wealth on the EA score and our standard controls. Column [1] of Panel B in Table 9 establishes the baseline coefficient by repeating the final specification in Table 4, but restricting the sample to those households with non-missing values for the asset ownership variables. In Columns [2] and [3], we include indicator variables for whether the household owns their home or has ever owned a business during the sample. In both cases, the coefficient on the EA score declines to 0.046, but remains statistically significant at the 5-percent level.

In Column [4] of Table 9, we include an indicator for stock ownership. This reduces the coefficient on the EA score substantially, from 0.049 to 0.016, a reduction of roughly 67%. Further, the coefficient becomes statistically insignificant. This suggests that stock market participation may be an important explanatory factor for the gene-wealth gradient. However, we caution against over-interpreting this result; in other samples with less severe age and retirement restrictions, the coefficient on the EA score is larger and remains statistically significant when stock market participation is controlled for, suggesting that stock market participation is likely to be only one of potentially many relevant factors explaining the relationship between the EA score and wealth.

Finally, in Column [5], we include all three investment controls simultaneously. Together, they reduce the coefficient on the EA score to 0.018, which is not statistically significant. This offers preliminary evidence that investment decisions over the life-cycle, broadly defined, may be an important mediator of the gene-wealth gradient. We again emphasize that these results should be interpreted with care. For example, the empirical specifications in Panel B of Table 9 may be biased by measurement error in the right-hand-side variables. However, these results may be suggestive of possible relevant mechanisms relating the EA score to wealth. Motivated by these findings, we next evaluate the extent to which the EA score is related to financial decision-making.

5.4 Extreme Beliefs and Planning Horizons

An important element of financial decision-making is an assessment of the risks and uncertainties associated with the macroeconomy and the payoffs to alternative financial choices. Yet, inferring the likelihood of uncertain events can be difficult. Despite the typical assumption of rational expectations, it has long been recognized that individuals may have trouble forming accurate beliefs about probabilistic outcomes (Savage, 1954; Kahneman and Tversky, 1972). Further, a well-documented challenge for prudent savings and investment decisions is the complexity associated with intertemporal choices. Thinking about the distant future is difficult; as the planning horizon increases so too does the uncertainty around financial needs, investment and employment opportunities, family composition, and a host of other important considerations. In this section, we evaluate whether the EA score is associated with an aptitude for abstract and complicated financial decisions.

Recent literature examines the role of subjective expectations in economic decisions such as human capital investments (Wiswall and Zafar, 2015) and stock market participation (Arrondel, Calvo Pardo, and Tas, 2014). Another set of papers demonstrates links between subjective beliefs and investment behaviors that impact household wealth (Lillard and Willis, 2001; Dominitz and Manski, 2007; Hudomiet, Kézdi, and Willis, 2011).[29] Lumsdaine and Potter van Loon (2017) study differences in how individuals report beliefs about stock market returns, arguing that their findings reflect heterogeneity in individuals' understanding of the laws of probability. In related work Lusardi, Michaud, and Mitchell (2017) demonstrate that heterogeneity in returns to savings, which are plausibly determined by financial knowledge, can explain a substantial proportion of wealth inequality.

We begin by investigating whether the average household EA score is associated with differences in beliefs about macroeconomic events that are relevant for financial choices. The HRS data are uniquely well-suited for this analysis, as most respondents are repeatedly asked to provide subjective probabilities of a range of events. Individuals are asked to provide a probability on a scale of 0 to 100 for the following three macroeconomic events:

- **Stock Market Goes Up**: "By next year at this time, what is the percent chance that mutual fund shares invested in blue chip stocks like those in the Dow Jones Industrial Average will be worth more than they are today?"
- **Economic Depression**: "What do you think are the chances that the U.S. economy will experience a major depression sometime during the next 10 years or so?"
- **Double Digit Inflation**: "And how about the chances that the U.S. economy will experience double-digit inflation sometime during the next 10 years or so?"

First, we construct one (of possibly many) measures of "objectively correct" responses to these questions. Our objective benchmark probability for the stock market going up in a single year is 71 percent, which is the probability the S&P 500 increases in value in a given year for the period 1992-2015. There is no common definition of an economic depression, but

[29]Hurd (2009) provides a review of subjective probabilities reported in household surveys such as the HRS. A number of researchers have used the HRS to study cognition, probabilistic thinking and investment decisions (Lillard and Willis, 2001; Kézdi and Willis, 2009, 2003). Another set of related studies focuses on cognitive decline and retirement decisions (Rohwedder and Willis, 2010; Kézdi and Willis, 2013; Delavande et al., 2006; Delavande, Rohwedder, and Willis, 2008).

clearly this refers to an unusually severe period of economic contraction. We use data from the Federal Reserve Bank of Saint Louis on annual real GDP growth over the period 1948-2016, and define an unusually severe contraction as a year with growth less than or equal to -0.73 percent, which is the 25th percentile of the distribution of growth rates for negative-growth years. Based on this metric, the unconditional probability of a severe contraction is 4.4 percent per year, which implies a 36 percent probability for such an event over a 10 year period. Finally, the Bureau of Labor Statistics reports two years with double digit inflation (1980, 1981) over the period 1958-2015. This implies an approximate probability of 3.4 percent for double digit inflation in any year, or about a 29 percent chance for double digit inflation over a 10 year period.[30]

Panel A of Table 10 provides estimates of the association between the average household EA score and individual beliefs about the probabilities of these macroeconomic events. We use the average household score rather than the individual EA score so as to be consistent with our analysis in Section 5.3, and to avoid decisions about intra-household information transfers. Our first measure is the absolute value of the deviation between the respondent's subjective probability and the objective probability. We regress this deviation on our standard controls and the EA score in Column [1]. For all three events, higher values of the polygenic score are associated with a statistically significant reduction in the deviation between the respondent's subjective probability and the objective probability. For example, in Column [1] of Panel A, the coefficient estimate of -0.567 suggests that a one standard deviation increase in the EA score is associated with a reduction in the deviation from the objective stock market increase probability of over one half of one percentage point. Coefficients of -0.550 and -1.054 are estimated for the depression and double-digit inflation questions, respectively.

Columns [2]-[4] of Panel A in Table 10 examine binary outcomes indicating whether

[30] In results available from the authors, we show that main results relating the EA score to deviations from objective probabilities remain qualitatively similar for reasonably large intervals around the objective probabilities we use.

respondents answered with specific focal probabilities (0, 50, and 100, respectively). Using linear probability models, we relate these binary outcomes to the EA score. For all three events, we observe the same pattern of association: the EA score is negatively associated with providing a subjective probability indicating complete certainty (0 or 100), and is largely uncorrelated with providing a focal probability of 50 percent. The magnitudes of these associations are substantial. For example, findings on beliefs about a depression suggest that a one standard deviation increase in the EA score is associated with a 0.5 percentage point reduction in the probability of reporting a 0% probability that the economy will suffer a major depression in the next 10 years. For comparison, 7% of individuals report a 0% probability for this event. While we find no statistically significant association between the EA score and reporting a 100% probability that the stock market will increase, we do find a relationship between 100% beliefs about economic recessions and double-digit inflation.

These results suggest that individuals from households with lower polygenic scores are more likely to report beliefs that are at odds with objective probabilities. Moreover, lower scores are also associated with a greater tendency to report "extreme" beliefs. We next investigate whether the EA score is associated with the length of the financial planning horizon. The complexity of economic decisions increases with their scope, and households may be heterogeneous in the costliness of thinking about increasingly distant future periods. Those for whom such considerations are relatively low-cost will endogenously consider longer horizons. The HRS asks respondents about their planning horizons for spending and saving: "In deciding how much of their (family) income to spend or save, people are likely to think about different financial planning periods. In planning your (family's) saving and spending, which of the following time periods is most important to you (and your husband/wife/partner): the next few months, the next year, the next few years, the next 5-10 years, or longer than 10 years?" 13% of respondents report planning horizons of less than 1 year. 12% have a planning horizon of at least a year, but less than a few years. 30% have a planning horizon of a few years, 34% indicate horizons in the range of 5-10 years, and 11% have planning horizons of more than 10 years.

In Panel B of Table 10, we test whether the EA score predicts planning horizon responses. The dependent variable in Column [1] is a dummy variable equal to one if the planning horizon is greater than a few months. The estimated coefficient is statistically significant, and suggests that a one standard deviation in the EA score is associated with a 0.8 percentage point increase in the probability of reporting a planning horizon longer than a few months. Columns [2]-[4] repeat this exercise, but with dummies equal to one for increasingly longer horizons. The dummy dependent variable in Column [2] is equal to one if the reported horizon is "a few years", in [3] if "5-10 years", and in [4] if "longer than 10 years". In all but Column [4], the coefficient on the EA score is positive and significant at the 1% level. This suggests that the EA score is predictive of longer planning horizons for all but the longest horizon.

The results linking the length of the planning horizon to the EA score are consistent with an interpretation that higher EA score households are better able to think about complex and abstract decision problems. Alternatively, these results could be interpreted as an association between the EA score and patience. However, in results available from the authors and using the HRS questions designed to elicit patience parameters, we find little variation between households that report the shortest and longest planning horizons. This suggests it is unlikely that the planning horizon results are due to patience. Gabaix and Laibson (2017) provide a theoretical foundation for our interpretation. They demonstrate that infinitely patient, Bayesian households that receive noisy, unbiased signals about future events will behave *as if they are impatient*. A consequence of their model is that households that receive more precise signals will appear to behave as if they are more patient than others, even though all households are equally (infinitely) patient.

In Appendix C, we provide several additional analyses. First, we use the cognitive test score administered to HRS respondents to evaluate whether the gene-wealth gradient works through cognition. In particular, we include the test score as an additional control and find that it does little to mediate the gene-wealth gradient. This is not surprising given why and how the test is constructed: to capture cognitive decline through memory tasks and simple factual questions. Second, it is possible that reported macroeconomic beliefs are not related to individual behavior in a meaningful way, making these results interesting but not particularly useful for understanding the potential underlying mechanisms linking the EA score to financial decisions. This would be the case if either the HRS expectations questions do a poor job of eliciting true beliefs about these economic events, or if the events themselves were not relevant for the household's choice problem. In Appendix B, we show that these elicited beliefs do indeed predict relevant behaviors such as stock market participation, and are associated with wealth. Further, excessive optimism about the stock market is actually associated with *greater* wealth, likely due to an increase in participation. This suggests that the direction of incorrect beliefs is important for their overall impact on wealth.

5.5 Pensions

One consequence of the apparent relationship between genetic endowments and financial decisions is that individuals with low EA scores may benefit from outsourcing certain economic choices, such as saving and investment decisions. Defined benefit pensions, which may be provided by one's employer, offer one form of outsourcing by providing an employee a guaranteed stream of income in retirement without requiring the individual to choose the contribution rate or underlying investment allocations. Defined benefit plans effectively reduce the impact of the household's financial decisions on accumulated wealth by ensuring a minimal level of resources at retirement. We investigate whether the reduced autonomy associated with defined-benefit pensions alters the relationship between genetic ability and wealth.[31]

Over half of households (57%) have a defined-benefit pension with an average present

[31]Because we focus only on retired households, our definition of defined-benefit plan participation is whether the household reports receiving income from a defined-benefit pension in that household-year. We also winsorize defined-benefit pension wealth at the 1st and 99th percentiles.

discounted value of $234,021. One primary concern is that pension participation is not randomly assigned. As a first step, we regress an indicator for defined-benefit pension participation on the average household EA score. Column [1] of Table 11 shows that after including our standard set of controls, there is no economically or statistically significant relationship between the EA score and defined-benefit pension participation. Column [2] shows that, conditional on participation in a defined-benefit pension plan, defined-benefit pension wealth (the present value of pension income) is also unrelated to the EA score. In general, selection into careers based on defined-benefit pension benefits appears to be uncorrelated with the EA score after controlling for education.

Columns [3] and [4] of Table 11 investigate whether participation in a defined-benefit plan mitigates the role of the EA score in wealth accumulation. Column [3] shows that the coefficient on the EA score remains large and statistically significant when an indicator for defined-benefit pension wealth is included.[32] In Column [4], we also include an interaction between the EA score and the pension-participation dummy. We also include interactions between the pension-participation dummy and all principal components variables to account for possible population stratification in obtaining defined-benefit pensions. The results are striking. The coefficient on the interaction is negative and statistically significant, and is economically large. For households that participate in a defined-benefit plan, the coefficient on the EA score is 0.029, compared to 0.125 for households that do not participate in a defined-benefit plan. Put differently, the relationship between the EA score and wealth is over four times as large for households that have more autonomy over their savings and investment choices. This offers strong evidence in support of the hypothesis that the gene-wealth association documented in this paper is in part determined by a household's difficulty in making wise financial choices.

[32]Note that the coefficient of 0.39 on the defined-pension dummy variable in Column [3] should not be interpreted in isolation, since this specification also includes interactions between this dummy and the principal components of the genetic data.

6 Conclusions

We study the genetic endowments linked to educational attainment, summarized as a linear index called a polygenic score (EA score). Using data from the HRS, we demonstrate that the average EA score in a household strongly and robustly predicts wealth at retirement. The estimated gene-wealth gradient is not fully explained by flexibly controlling for education and income, nor by parental transfers (bequests) and parents' education, which may proxy for parental investments. We find the EA score is related to risk preferences and mortality, and strongly predicts stock ownership. Stock market participation appears to substantially mediate the gene-wealth association. Lower EA scores are associated with less accurate beliefs about macroeconomic probabilities, as well as shorter planning horizons. Finally, the EA score is much more strongly related to wealth within a subsample of individuals who do not receive defined-benefit pension benefits, and who presumably have greater autonomy over their financial decisions.

The associations we report not only help us to explain the gene-wealth gradient, but may also suggest why these particular genetic markers are associated with education. In particular, the finding that the EA score is related to probabilistic thinking, planning horizons, and decision-making under uncertainty may be useful for understanding the sources of heterogeneity in human capital accumulation. However, we offer important caveats for such an interpretation of these findings. First, measurement error in income, education, and parental transfers may lead us to incorrectly ascribe part of the gene-wealth gradient to other factors that would be unrelated if such variables were correctly measured. Second, genetic measures are likely endogenous to family environment, so one must be careful before assigning a causal interpretation to the gene-outcome gradients that we observe. Third, the polygenic score does not fully explain the amount of education that twin studies have suggested is heritable. Future GWAS will likely estimate more precise genetic associations which could lead to stronger empirical relationships between a polygenic score and completed schooling, and which could alter the empirical relationships documented here.

Economic research using information on genetic endowments is useful for understanding what has heretofore been a form of unobserved heterogeneity that persists across generations. Studies that ignore this type of heterogeneity when studying the intergenerational persistence of economic outcomes, such as income or wealth, could place too much weight on other mechanisms such as attained education or direct monetary transfers between parents and children. The use of observed genetic information can therefore help economists to develop a more accurate and complete understanding of inequality across generations.

Studying how genetic endowments implicated in one outcome, in this case education, relate to other outcomes, such as wealth, leads to a more complete picture of how these endowments function, including how they interact with policy-relevant environmental factors. Our results on pensions and the gene-wealth gradient are an illustration of how environmental factors can modify the relationship between genetic endowments and key economic outcomes. This is one example of what is often referred to as a *gene by environment* interaction.

Importantly, demonstrating a genetic basis for behavioral outcomes in no way precludes the possibility of effective public policies. A better understanding of why individuals with higher polygenic scores achieve better results may allow for a better design of policies and educational environments that help to improve outcomes. For example, it may be that children with lower polygenic scores begin to face challenges at particular ages or struggle to meet specific educational milestones. In that case, we could better target educational policies to help alleviate these roadblocks. In this manner, the future of genetic research is likely to be just as concerned with nurture as it is with nature. In short, studying how genes are connected to choices and behavior is important because it provides guidance for creating the kinds of environments where everyone, regardless of genetic endowments, has the opportunity to thrive.

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7 Tables and Figures

Table 1: Summary Statistics

Variable	Mean	SD	N
Year of Birth			
Female	1935.10	5.59	2369
Male	1933.04	5.76	2015
Years of Education			
Female	12.67	2.30	2369
Male	12.74	2.96	2015
Highest Degree			
Female			
No Degree	0.16	0.37	2369
GED	0.04	0.19	2369
High School Degree	0.60	0.49	2369
Some College	0.04	0.19	2369
College Degree	0.10	0.30	2369
MA	0.05	0.22	2369
Professional Degree	0.01	0.09	2369
Male			
No Degree	0.19	0.39	2015
GED	0.06	0.24	2015
High School Degree	0.47	0.50	2015
Some College	0.03	0.18	2015
College Degree	0.13	0.34	2015
MA	0.08	0.27	2015
Professional Degree	0.04	0.18	2015
Household Income (× \$1,000)			
Mean	2,315.95	.	2377
Std. Dev.	1,405.43	.	2377
Avg. Years Top-Coded	12.67	.	2377
25th Percentile	1,287.80	.	2377
50th Percentile	2,255.30	.	2377
75th Percentile	3,082.30	.	2377
Household Wealth (× \$1,000)			
Mean	900.17	.	5621
Std. Dev.	1,411.22	.	5621
10th Percentile	168.74	.	5621
25th Percentile	303.82	.	5621
50th Percentile	593.64	.	5621
75th Percentile	1,031.48	.	5621
90th Percentile	1,706.83	.	5621
Median, No Housing	450.49	.	5621
Median, No Pensions	235.98	.	5621
Median, Neither	92.00	.	5621

Notes: Summary statistics for birth year, schooling, and highest degree completed are calculated separately for males and females. Income and wealth are computed at the household level. Additional statistics are found in Tables S1-S6 in the Appendix.

Table 2: Household EA Score Related to Key Economic Variables

	[1]	[2]	[3]	[4]	[5]	[6]
	Q1	Q2	Q3	Q4	Q4−Q1	Q4−Q1 p-value
Panel A						
Avg. Household EA Score and *Individual* Variables						
Female:						
Education	11.73	12.19	13.02	13.71	1.99	< 0.01
Father's Education	8.66	8.99	9.82	10.63	1.97	< 0.01
Mother's Education	9.34	9.48	10.37	10.62	1.28	< 0.01
Male:						
Education	11.58	12.23	13.17	13.96	2.38	< 0.01
Father's Education	8.59	9.01	9.65	10.47	1.89	< 0.01
Mother's Education	9.10	9.66	10.27	10.62	1.53	< 0.01
Panel B						
Avg. Household EA Score and *Household* Variables						
Avg. HH Income (in $1000)	2,132.02	2,260.31	2,361.22	2,513.39	381.37	< 0.01
Avg. HH Wealth (in $1000)	603.87	771.27	909.93	1,082.24	478.36	< 0.01

Notes: This table relates the EA score to key economic variables. Columns [1]-[4] separate individuals into quartiles of the individual EA score distribution and report average values of own and parents' education, separately for males and females, for the genotyped individuals belonging to a household in the sample. Column [5] reports the difference in average values between the fourth and first quartiles, while Column [6] displays the p-value associated this difference. Panel B conducts a similar exercise for household wealth and income.

Table 3: EA Score and Selection

	[1]	[2]	[3]	[4]	[5]	[6]
Individual EA Score and Individual Variables	Q1	Q2	Q3	Q4	Q4−Q1	Q4−Q1 p-value
Panel A: Retired Households, Ages 65-75 (Main Sample)						
Male	0.38	0.41	0.41	0.43	0.045	0.057
Birth Year	1935.19	1934.65	1934.28	1934.00	-1.19	< 0.01
Age	69.96	70.05	70.09	70.29	0.33	< 0.01
Panel B: Retired Households, Ages 55-85						
Male	0.38	0.39	0.41	0.42	0.04	0.049
Birth Year	1934.89	1934.65	1933.30	1932.90	-1.98	< 0.01
Age	70.89	71.13	71.85	72.31	1.42	< 0.01
Panel C: All Households, Ages 50-75						
Male	0.42	0.43	0.42	0.44	.026	0.13
Birth Year	1939.98	1939.64	1939.17	1939.31	-0.68	0.02
Age	63.64	63.40	63.62	63.43	-0.22	0.05
Panel D: All Households, Ages $\leq$ 85						
Male	0.40	0.41	0.41	0.43	0.02	0.12
Birth Year	1938.56	1938.22	1937.28	1937.39	-1.17	< 0.01
Age	65.65	65.83	66.35	66.36	0.72	< 0.01

Notes: This table assesses the relationship between the EA score and gender, birth year and age in alternate samples. Columns [1]-[4] separate individuals into quartiles of the individual EA score distribution and report average values of demographic variables for each quartile. Column [5] reports the difference in average values of each variable between the fourth and first EA quartiles, while Column [6] reports the p-values associated with these differences. In Panel A, we consider our baseline sample of retired households with members aged 65-75. In Panel B, we report statistics for a larger sample that includes retired households with members aged 55-85. In Panel C, we consider a sample that includes all households (retired and non-retired households) with members aged 50-75. Panel D includes all households with members aged no more than 85.

Table 4: AVERAGE HOUSEHOLD EA SCORE AND HOUSEHOLD WEALTH

Dep. Var: Log Wealth	[1]	[2]	[3]	[4]	[5]	[6]	[7]
EA Score	0.246***	0.221***	0.218***	0.085***	0.070***	0.179***	0.047**
	(0.022)	(0.020)	(0.020)	(0.021)	(0.023)	(0.020)	(0.022)
Male Educ				0.061***			
				(0.009)			
Female Educ				0.122***			
				(0.010)			
Log Income						0.316***	0.263***
						(0.039)	(0.038)
Obs.	5621	5621	5621	5621	5621	5308	5308
R^2	0.054	0.251	0.279	0.368	0.435	0.349	0.479
Standard Controls		X	X	X	X	X	X
Principal Comp.			X	X	X	X	X
Years of Educ.				X			
Full Educ. Controls					X		X

Notes: This table presents estimates from regressions of log household wealth on average household EA score and varying sets of controls. Column [1] includes no controls. Column [2] includes controls for age, birth cohort, sex of respondent, and calendar year, as described in Section 4.2. Column [3] adds controls for principal components of the genetic data for genotyped household members. Column [4] adds years of education separately for both female and male household members. Column [5] replaces the two schooling variables with our full set of education controls (dummies for years of education, degree dummies and interactions as described in Section 4.2). Column [6] includes the log of total household income, but excludes any controls for education. Column [7] includes our full set of controls including the detailed education variables and the log of total household income. Significance stars ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. Standard errors are clustered at the family level.

Table 5: Average Household EA Score and Household Wealth: Robustness

Dep. Var: Log Wealth	[1]	[2]	[3]	[4]	[5]	[6]
FR EA Score	0.083***	0.070***				
	(0.025)	(0.025)				
Non FR EA Score	0.023	0.019				
	(0.023)	(0.022)				
Avg. EA Score			0.079***	0.057***	0.071***	0.044*
			(0.018)	(0.018)	(0.025)	(0.023)
Log Income (SSA)		0.211***		0.284***		0.197***
		(0.056)		(0.029)		(0.038)
Log Income (HRS)						0.221***
						(0.030)
Obs.	1927	1870	18925	17563	3993	3833
R^2	0.476	0.507	0.358	0.387	0.454	0.512
Include Non-Retired HH			X	X		
Standard Controls	X	X	X	X	X	X
Principal Comp.	X	X	X	X	X	X
Full Educ. Controls	X	X	X	X	X	X

Notes: This table provides estimates from three different robustness checks. In each case, log household wealth is the dependent variable and we only show results analogous to estimates in Columns [5] (with the full set of education controls) and [7] (full set of education controls and log income) of Table 4. Columns [1] and [2] provide estimates from models where we condition on two EA scores per household, that of the financial respondent (FR) and of the non financial respondent (NFR). Columns [3] and [4] provide estimates from models where we have increased the sample to include non-retired households. Columns [5] and [6] provide estimates of models that include two measures of income, the SSA lifetime income measure used in our main analyses, along with the HRS measure of contemporaneous household income. Significance stars ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. Standard errors are clustered at the family level.

Table 6: INHERITANCES AND PARENTAL EDUCATION

Dep. Var: **Log Wealth**	[1]	[2]	[3]	[4]
EA Score	0.070***	0.064***	0.062***	0.058**
	(0.023)	(0.022)	(0.023)	(0.023)
Any Inheritance		-1.042***		-0.990***
		(0.172)		(0.171)
Log Total Inheritance		0.121***		0.116***
		(0.016)		(0.016)
Father Education (Male)			0.009	0.007
			(0.007)	(0.007)
Father Education (Female)			0.021***	0.019***
			(0.007)	(0.007)
Mother Education (Male)			0.014*	0.010
			(0.007)	(0.007)
Mother Education (Female)			-0.009	-0.012
			(0.007)	(0.007)
Obs.	5621	5621	5621	5621
R^2	0.435	0.456	0.442	0.461
Standard Controls	X	X	X	X
Principal Comp.	X	X	X	X
Years of Educ.	X	X	X	X
Full Educ. Controls	X	X	X	X

Notes: This table presents estimates from regressions of log household wealth on average household EA score and varying sets of controls. Column [1] includes the full set of controls from Column [5] of Table 4. Column [2] includes an indicator for ever receiving an inheritance in the HRS, as well as the log of received inheritances (set to 0 for those without an inheritance). Column [3] includes controls for parents' years of education, along with separate dummy variables indicating missing values for each of the four parental education variables. Column [4] includes both the inheritance variables and the parental education variables. Significance stars ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. Standard errors are clustered at the family level.

Table 7: Mortality

Dep. Var:	**Observed Mortality**			**Exp. Mortality Pr(Live to 75)**		
	All Ind.	**Females**	**Males**	**All Ind.**	**Females**	**Males**
	[1]	[2]	[3]	[4]	[5]	[6]
EA Score	-0.003*	-0.005***	0.000	0.418	0.659*	-0.316
	(0.001)	(0.002)	(0.002)	(0.286)	(0.370)	(0.482)
Obs.	26733	14780	7419	29119	17433	11686
R^2	0.035	0.032	0.029	0.118	0.130	0.150

Notes: This table investigates the relationship between the EA score, mortality, and mortality expectations. Column [1] presents estimates of a linear probability model for death in the next period for all individuals in our sample, while Columns [2] and [3] perform this separately for females and males, respectively. The specifications in Columns [1]-[3] include the following controls: individual principal components and dummy variables for each possible age, birth year, number of years of schooling, and degree. In Columns [4]-[6], the outcome variable is the reported probability an individual expects to live to age 75, again shown for the full sample and then separately for females and then males. The control set for these specifications is the same as our standard full control set in Column [5] of Table 4. Significance stars ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. Standard errors are clustered at the family level.

Table 8: Risk Aversion

Dep. Var:	**Risk Aversion: Indicator**			**Risk Aversion categories**		
	Income	**Inheritance**	**Business**	**Income**	**Inheritance**	**Business**
	[1]	[2]	[3]	[4]	[5]	[6]
EA Score	-0.022***	-0.004	-0.027**	-0.045***	0.017	-0.057**
	(0.007)	(0.012)	(0.011)	(0.015)	(0.029)	(0.027)
Obs.	10512	2951	2912	10512	2951	2912
R^2	0.105	0.210	0.246			
Mean outcome	0.39	0.51	0.47			
Standard Controls	X	X	X	X	X	X
Principal Comp.	X	X	X	X	X	X
Full Educ. Controls	X	X	X	X	X	X

Notes: This table presents estimates from regressions of measures of individual risk tolerance on the EA score and various controls. Risk tolerance is elicited from questions based on risky gambles over labor income, inheritance wealth, and business wealth. In Columns [1]-[3], the dependent variable is an indicator that takes a value of 1 for individuals that never choose the risky option over a guaranteed outcome. In Columns [4]-[6] we report estimates from ordered probit models where the outcome is a categorical variable that takes one of six values depending on the riskiest gamble that an individual accepts, with higher values indicating greater risk aversion. Significance stars ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. Standard errors are clustered at the family level.

Table 9: Average Household EA Score and Portfolio Decisions

Panel A Dep. Var:	**Owns House** [1]	**Owns Business** [2]	**Owns Stocks** [3]	**Owns House** [4]	**Owns Business** [5]	**Owns Stocks** [6]
EA Score	0.003	0.005	0.052***	-0.008	-0.001	0.040***
	(0.008)	(0.006)	(0.011)	(0.008)	(0.006)	(0.011)
Log Income	0.033***	-0.004	0.062***	0.002	-0.021**	0.021
	(0.008)	(0.006)	(0.011)	(0.008)	(0.008)	(0.013)
Lagged Log Wealth				0.122***	0.047***	0.151***
				(0.009)	(0.007)	(0.016)
Obs.	6460	6460	5450	4649	4649	4196
R^2	0.304	0.160	0.348	0.399	0.217	0.435
Mean outcome	0.84	0.08	0.46	0.83	0.08	0.47
Standard Controls	X	X	X	X	X	X
Principal Comp.	X	X	X	X	X	X
Full Educ. Controls	X	X	X	X	X	X

Panel B Dep. Var: Log Wealth	[1]	[2]	[3]	[4]	[5]
EA Score	0.049**	0.046**	0.046**	0.016	0.018
	(0.023)	(0.021)	(0.022)	(0.021)	(0.019)
Owns Stocks				0.624***	0.507***
				(0.034)	(0.029)
Has Business			0.594***		0.530***
			(0.049)		(0.044)
Owns Home		0.887***			0.741***
		(0.054)			(0.052)
Obs.	4912	4912	4912	4912	4912
R^2	0.487	0.551	0.504	0.540	0.599
Standard Controls	X	X	X	X	X
Principal Comp.	X	X	X	X	X
Full Educ. Controls	X	X	X	X	X
Log Income	X	X	X	X	X

Notes: Panel A of this table presents estimates from regressions of indicators for ownership of different asset types on the EA score and various controls. Panel B presents estimates from regressions of log household wealth on the EA score, indicators for ownership of different asset types, and various controls. Significance stars ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. Standard errors are clustered at the family level.

Table 10: Extreme Beliefs and Planning Horizons

Panel A	**The EA Score and Beliefs**			
Dep. Var:	**Deviation**	**Prob=0**	**Prob=0.5**	**Prob=1**
	[1]	[2]	[3]	[4]
		Stock Market Goes Up		
EA Score	-0.567***	-0.006***	-0.003	-0.002
	(0.162)	(0.002)	(0.003)	(0.001)
Obs.	35842	35842	35842	35842
R^2	0.097	0.062	0.030	0.048
Mean outcome	28.31	0.05	0.30	0.04
		Depression		
EA Score	-0.550***	-0.005**	-0.003	-0.008***
	(0.138)	(0.002)	(0.003)	(0.002)
Obs.	35912	35912	35912	35912
R^2	0.088	0.047	0.037	0.072
Mean outcome	24.94	0.07	0.26	0.06
		Double Digit Inflation		
EA Score	-1.054***	-0.004**	-0.005	-0.011***
	(0.193)	(0.002)	(0.004)	(0.002)
Obs.	22604	22604	22604	22604
R^2	0.080	0.057	0.044	0.072
Mean outcome	26.10	0.06	0.34	0.07
Panel B	**The EA Score and Planning Horizons**			
Dep. Var:	**PH$\geq$ 1 Yr.**	**PH$\geq$ Few Yrs.**	**PH$\geq$ 5-10 Yrs.**	**PH$>$ 10**
	[1]	[2]	[3]	[4]
EA Score	0.008***	0.011***	0.013***	0.004
	(0.003)	(0.004)	(0.004)	(0.003)
Obs.	27752	27752	27752	27752
R^2	0.072	0.081	0.077	0.045
Mean outcome	0.87	0.75	0.45	0.11
Standard Controls	X	X	X	X
Principal Comp.	X	X	X	X
Full Educ. Controls	X	X	X	X

Notes: Panel A of this table presents estimates from regressions of beliefs about probabilities of three macroeconomic events on the EA score and various controls. Separate estimates are given for three distinct macroeconomic events: an increase in the stock market over the next year, a major depression in the next 10 years, and double-digit inflation in the next 10 years. In Column [1] the dependent variable is the absolute value of the deviation of the respondent's belief from an "objective" probability (as described in Section 5.5). The outcome variables in Columns [2], [3] and [4] are indicators for providing subjective probabilities of 0, 0.5 and 1, respectively. Panel B presents estimates from regressions of indicator variables for the length of a respondent's financial planning horizon on the EA score and various controls. In Column [1] the dependent variable is an indicator for reporting a planning horizon greater than or equal to one year. In Columns [2], [3] and [4], the dependent variables are indicators for horizons of "greater than or equal to a few years;" "greater than or equal to 5-10 years;" and "greater than 10 years," respectively. Significance stars ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. Standard errors are clustered at the family level.

Table 11: Pensions and Household Wealth

Dep. Var:	**Has Pension** [1]	**Pension Wealth** [2]	**Log Wealth** [3]	**Log Wealth** [4]
EA Score	0.003	0.030	0.069***	0.125***
	(0.011)	(0.035)	(0.022)	(0.035)
DB Pension			0.385***	0.181***
			(0.035)	(0.051)
EA Score x DB Pension				-0.096***
				(0.036)
Obs.	5621	3226	5621	5621
R^2	0.215	0.400	0.460	0.474
Mean outcome	0.57	$234,021		
Standard Controls	X	X	X	X
Principal Comp.	X	X	X	X
Full Educ. Controls	X	X	X	X

Notes: Columns [1]-[2] of this table present estimates from regressions of defined benefit (DB) pension participation and log pension wealth (conditional on participation) on the EA score and various controls. Columns [3]-[4] present estimates from regressions of log household wealth on the EA score, DB pension participation, an interaction between the EA score and pension participation, and various controls. Significance stars ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. Standard errors are clustered at the family level.

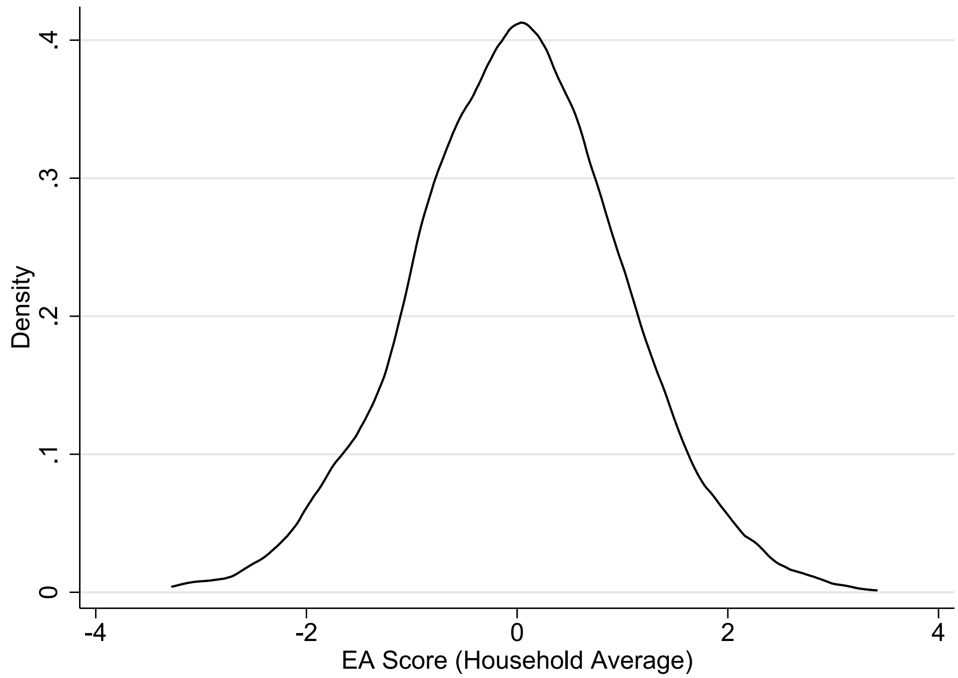
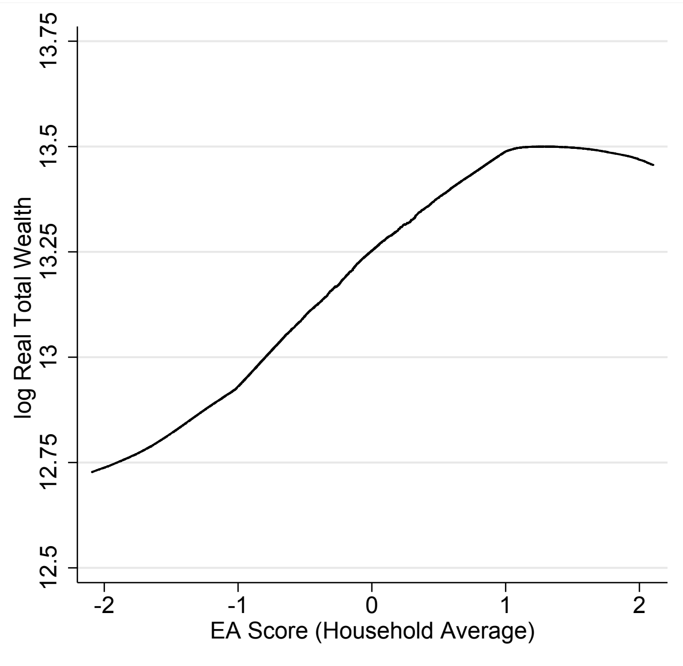
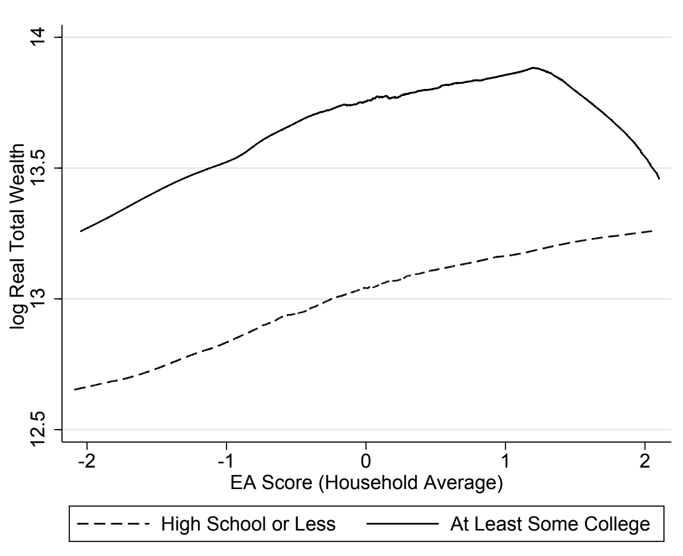


Figure 1: Distribution of Household Average EA Score



Panel A: Full Sample



Panel B: Stratified by Education

Figure 2: *Notes*: Panel A plots average household EA score versus log household wealth using data for all household-year observations in the analytic sample. Panel B plots the same relationship for two subsamples of households, the first with a maximum education level of a high school degree or less and the second with at least one member having at least a college degree.

Online Appendix:

"Genetic Endowments and Wealth Inequality"

By: Daniel Barth, Nicholas W. Papageorge and Kevin Thom

A Wealth Data and Additional Summary Statistics

A.1 Retirement Wealth

The wealth data used in this paper are largely constructed from the RAND wealth and income files. The RAND files are carefully cleaned and consistently coded by RAND Corporation and are available for public use. The RAND files have been used in both academic and industry publications, and ensure comparability and consistency across HRS waves and research projects. We refer the reader to the RAND codebook and documentation for further details.

One important shortcoming of the RAND wealth files is the exclusion of employer-sponsored retirement plan account balances. While the RAND wealth files do include the balances of IRAs and other non-employer-sponsored plans, wealth accumulated in employer-sponsored 401k, 403(b), and other such accounts are not included. For households at or near retirement, such accounts can be a significant source of wealth. Further, such accounts may be the only vehicles through which households invest in the stock market, and measures of stock market participation will understate true participation if these plans are not considered.

Unfortunately, data on employer-sponsored retirement plans are not asked in every wave, and are sometimes inconsistently coded across waves. The remainder of this section focuses on our methodology for coding retirement account balances and stock market participation inferred from those accounts. Broadly speaking, there are two types of retirement plans: defined-benefit plans, such as traditional pensions (which the HRS calls type A plans), and defined contribution plans, such as 401k and 403(b) plans (which the HRS calls type B plans). We discuss each type of plan in turn.

A.1.1 Defined Benefit Plans

To deal with issues arising from type A style retirement plans, our sample includes only households fully in retirement (households in which no member of the household is currently working). We exclude working households because expected benefits from defined-benefit pension plans are likely to be both an important source of wealth and noisily measured. For retired households, our assumption is that those who report receiving pension income were included in defined-benefit pension plans at some point during their working lives, and those who do not receive pension income in retirement were not included in such plans. To the extent that households misreport pension income, for example if income from an annuity converted from a 401k plan is reported as pension income, or if households have delayed receiving pension benefits until some future date, our assignment of households participating in type A plans will be biased. Further, because the household earns a guaranteed stream of income regardless of the underlying investments that support that income (and because we do not observe these underlying investments), we do not consider a household's participation in type A pension plans to be participation in the stock market.

We include retirement income in our household wealth measure by calculating the price of an actuarially fair annuity based on the entirety of household retirement income, which includes pension income, annuity income, and income from social security. We follow Yogo (2016) by calculating the present discounted value of this income based on a 1.5% annual risk-free rate of return, and discount income in each year by the probability of the recipient surviving until that year.[33] Specifically, we calculate the present value of retirement income, P_t, as:

$$P_t = Y_t \sum_{s=1}^{T-t-1} \left[\prod_{u=1}^{s} p_{t+u} R^{-1} \right], \tag{4}$$

where Y_t is total retirement income, p_t is the recipient's survival probability in period t and is a function of gender, birth cohort, and age, and $R = 1.015$ is the annual risk-free rate of return.

A.1.2 Defined Contribution Plans

Wealth in defined contribution style plans is a bit trickier. Households may have plans associated with multiple previous employers. To calculate comprehensive measures of wealth and stock market participation, we would like to know both the balances and asset allocations of all employer-sponsored type B plans from all previous jobs. Unfortunately, this is not always possible.

In years 1996, 1998, and 2002-2010 (comprising even-numbered years), we have the highest quality data on total balances in employer-sponsored type B retirement plans.[34] In these years, our wealth data include balances of employer-sponsored plans that are still maintained through that employer, and have not been converted to annuities or rolled over into IRAs.

[33] We differ from Yogo (2016) in that we use the probability of death of the individual receiving the income, rather than of the female partner.

[34] In 2012, the pension data were changed to an entirely new format.

The HRS refers to such plans as *dormant plans*. Unfortunately, the value of dormant plans at employers prior to retirement are not asked in 1992, 1994, and 2000.

Dormant plans also present problems for measurement of stock market participation. While in years 2002-2010 the stock allocation within a respondent's retirement plan at the current employer is observable for working households, the stock allocation in dormant plans for retired households is not. Thus, for retirement plans at current or former employers, only stock market participation for plans at the current employer are included in our measure of stock market participation. Because our sample includes only retired households, stock market allocations at employer-sponsored plans contribute negligibly to our stock market ownership variable.

A.2 Additional Summary Statistics

This appendix provides additional summary statistics for the genotyped versus non-genotyped samples, demographics by household structure, income and wealth, and the potential mechanisms studied in Section 5. Table S1 documents differences in birth year, education, and other variables between the genotyped and non-genotyped samples. Genotyped individuals tend to be older, more educated, and belong to wealthier households. Table S2 presents the mean and standard deviation of demographic variables such as birth year, years of schooling, and highest degree earned. These are reported for all households in our sample and separately by household structure.

Panel A of Table S3 shows the distribution of lifetime labor earnings for all households and by household structure: coupled, male only, and female only households. Table S4 shows the distribution of various measures of household wealth: total wealth, total wealth excluding housing wealth, total wealth excluding the present value of retirement income, and total wealth excluding both retirement wealth and housing. Table S5 presents the mean, median, 75^{th} percentile, and 90^{th} percentile of each individual component of household wealth for the full sample for all household-years. We also calculate the share of total real wealth in each component for each household-year, and present the median and mean values of these shares.

Table S6 shows summary statistics for the various mechanisms that may help to explain the gene-wealth gradient. Panel A presents statistics on the fraction of households that receive an inheritance, the (total) amount of inheritances received for households that receive them, and the household average of parental education (years of schooling). Panel B reports summary statistics related to mortality. In particular, we examine the annual death rate for individuals in our main sample (excluding years before genotyping), and the subjective probability of living until the age 75, which is elicited multiple times per individual. Panel C reports summary statistics for measures of risk aversion. Specifically, Panel C shows the fraction of households that fall within each risk aversion bin (based on the gambles they would accept and reject) for the labor income gamble, the business wealth gamble, and the inheritance gamble. Panel D reports the mean and standard deviation of home ownership, business ownership, and stock market participation. Stock market participation includes equity investments in retirement accounts, mutual funds, or in individually held stocks.

Panel E of Table S6 reports summary statistics related to beliefs about macroeconomic events: the probability the stock market appreciated over the following year, the deviation of this belief from the objective estimate based on historical data, and whether the respondent reports a belief of 0% or 100% (extreme beliefs), or of 50% (a focal belief that may represent uncertainty). Similar statistics are reported for the likelihood of a major (economic) depression and double-digit inflation. Panel E also reports the distribution of the reported financial planning horizon. Finally, panel F reports the fraction of households that receive defined-benefit pension income, and the present discounted value of lifetime defined benefit income.

Appendix Table S1: Selection into Genotyping

	Genotyped	Non-Genotyped	Δ p-value
Birth Year	1938.39	1941.39	0.00
Education	12.58	11.94	0.00
Male	0.41	0.45	0.00
Total Income (in $1000)	1,076.69	841.67	0.00
Wealth (in $1000)	722.90	457.54	0.00
N (Max)	12,505	30,699	

Notes: This table provides summary statistics for the genotyped and the non-genotyped individuals in the HRS data. Wealth is measured once per individual when the individual's household is first observed.

Appendix Table S2: Summary Statistics — Birth Year and Education

	All Households (2369)		Female Only (541)		Male Only (187)	
	Mean	SD	Mean	SD	Mean	SD
	[1]	[2]	[3]	[4]	[5]	[6]
Year of birth						
Female	1935.10	5.59	1933.96	5.85	.	.
Male	1933.04	5.76	.	.	1934.83	5.56
Years of Education						
Female	12.67	2.30	12.65	2.45	.	.
Male	12.74	2.96	.	.	12.56	3.18
No Degree						
Female	0.16	0.37	0.19	0.39	.	.
Male	0.19	0.39	.	.	0.17	0.38
GED						
Female	0.04	0.19	0.03	0.17	.	.
Male	0.06	0.24	.	.	0.11	0.31
High School						
Female	0.60	0.49	0.58	0.49	.	.
Male	0.47	0.50	.	.	0.46	0.50
4-Year Degree						
Female	0.10	0.30	0.08	0.27	.	.
Male	0.13	0.34	.	.	0.12	0.33
Masters						
Female	0.05	0.22	0.07	0.25	.	.
Male	0.08	0.27	.	.	0.06	0.25
Professional						
Female	0.01	0.09	0.02	0.13	.	.
Male	0.03	0.18	.	.	0.03	0.16

Notes: This table reports means and standard deviations (SD) for birth year, years of education, and indicator variables for highest degree obtained for household members examined in our main analytic sample. Summary statistics are presented for males and females in all households and then separately for female-only households and male-only households.

Appendix Table S3: Summary Statistics — Income

	Quantiles of Income (in $1000)							
Panel A	10	25	50	75	90	Mean	SD	N
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
All Households	569.86	1287.80	2255.30	3082.30	4034.19	2315.95	1405.43	2377
Coupled	941.32	1707.75	2546.66	3340.43	4272.74	2609.35	1362.69	1702
Female Only	192.82	565.01	1212.20	2029.72	2870.63	1435.51	1133.95	503
Male Only	429.36	1123.86	1767.46	2538.92	3584.53	1987.43	1397.68	172

	All Households		Coupled		Female Only		Male Only	
Panel B	Mean	SD	Mean	SD	Mean	SD	Mean	SD
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Non-Missing Income	0.93	0.26	0.93	0.25	0.93	0.26	0.92	0.27
Zero Income	0.00	0.05	0.00	0.00	0.01	0.10	0.01	0.08
Avg. Yrs. Top-Coded	12.67	12.55	15.58	12.47	3.50	7.72	10.72	11.40
Never Top Coded	0.27	0.44	0.15	0.36	0.68	0.47	0.22	0.42

Notes: This table reports summary statistics for the income measure used in our main analysis obtained from the Social Security Administration Master Earnings File data. Panel A provides information on the proportion of households with non-missing data, the proportion of households with zero income (conditional on having non-missing income data), average number of years that any household member reports top-coded income, the fraction of households never observed with a top-coded income observation, and average total real income (in $1,000s). In years in which a household member's income is top-coded, we replace the top-coded amount with the average of individual earned incomes greater than or equal to the top-coded amount in the Current Population Survey for that year. Income statistics are provided for all households and separately by household structure. Panel B reports quantiles of the income distribution (in $1000s) along with the mean and standard deviation of income by household structure.

Appendix Table S4: Summary Statistics — Wealth (in $1000)

	p10	p25	p50	p75	p90	Mean	SD
	[1]	[2]	[3]	[4]	[5]	[6]	[7]
TotalWealth	168.74	303.82	593.64	1031.48	1706.83	838.05	851.27
NoHousing	146.12	236.99	450.49	815.63	1373.81	727.80	1286.55
NoRet	1.39	75.08	235.98	574.86	1164.70	530.36	1236.09
NoHouseorRet	0.00	6.08	92.00	339.28	838.10	357.99	1105.99

Notes: This table reports summary statistics on the distribution of real wealth in our main sample. Measures of wealth include total real wealth, total wealth excluding housing, total wealth excluding retirement wealth (the present discounted value of retirement income), and total wealth excluding housing and retirement wealth. Each wealth measure is winsorized at the 1st and 99th percentiles. These statistics are calculated for the full analytical sample of 5,701 household-year observations.

Appendix Table S5: Wealth Distribution ($1000)

	p50	p75	p90	Mean	Median Share	Mean Share
Ret Plans (Employer)	0.00	0.00	0.00	3.18	0.00	0.00
Ret Inc (PV)	278.30	436.69	664.24	365.76	0.57	0.57
Real Estate	0.00	0.00	60.77	46.98	0.00	0.03
Business	0.00	0.00	0.00	48.32	0.00	0.02
IRAs	0.00	86.95	247.49	91.69	0.00	0.07
Stocks	0.00	32.45	202.56	87.78	0.00	0.05
Cash Equiv.	8.08	28.36	75.00	30.65	0.01	0.04
CDs	0.00	3.04	53.68	20.06	0.00	0.02
Bonds	0.00	0.00	0.00	14.60	0.00	0.01
Other Assets	0.00	0.00	21.63	18.31	0.00	0.01
Other Debts	0.00	0.06	5.06	2.32	0.00	0.01
Trusts	0.00	0.00	0.00	1.91	0.00	0.00
Home Value	126.98	216.33	363.63	168.67	0.18	0.32
Mortgage	0.00	0.00	64.00	16.95	0.00	0.13
Home Loan	0.00	0.00	0.00	2.48	0.00	0.00
Second Home	0.00	0.00	40.51	24.83	0.00	0.02
Second Mortgage	0.00	0.00	0.00	1.29	0.00	0.00

Notes: Summary statistics for different sources of wealth (in $1000s). For each household-year, we calculate the share of total wealth from each source, and Columns [5] - [6] report the median and mean shares. We note that although we report positive values for Mortgages, Home Loans, and Other Debts here, these are subtracted in the construction of total wealth. Note that Ret Plans (Employer) represent only retirement accounts that are still maintained by the employer despite the household being retired.

Appendix Table S6: Summary Statistics: Mechanisms

	Mean	SD	N
Panel A: Transfers	[1]	[2]	[3]
Any Inheritance	0.41	0.49	2556
Inheritance Amount (in $1000)	160.62	612.61	1054
Fathers' Education (HH Avg.)	9.47	3.20	2294
Mothers' Educ (HH Avg.)	9.95	2.79	2345
Panel B: Mortality	[1]	[2]	[3]
Mortality	0.04	0.20	26733
Mortality Expectations	67.39	26.10	29119
Panel C: Risk Aversion	[1]	[2]	[3]
Not take 50-50 Gamble			
Doubling Income or 10% Cut	0.39	0.49	10512
Take 50-50 Gamble			
Doubling Income or			
10% Cut (but not 20%)	0.22	0.42	10512
20% Cut (but not 33%)	0.17	0.37	10512
33% Cut (but not 50%)	0.10	0.30	10512
50% Cut (but not 75%)	0.07	0.26	10512
75% Cut	0.05	0.22	10512

Notes: This table reports means and standard deviations for additional variables used to investigate mechanisms underlying the estimated gene-wealth gradient. Each panel corresponds to an alternative mechanism. Mechanisms include Transfers (Panel A); Mortality (Panel B); Risk aversion (Panel C); Portfolio choices (Panel D); Beliefs and planning horizons (Panel E); and Defined-benefit pensions (Panel F). *This table continues onto the following page.*

Appendix Table S6: Summary Statistics: Mechanisms (continued)

	Mean	SD	N
Panel C: Risk Aversion (continued)	[1]	[2]	[3]
Not take 50-50 Gamble			
Doubling Business or 10% Cut	0.47	0.50	2912
Take 50-50 Gamble			
Doubling Business or			
10% Cut (but not 20%)	0.11	0.32	2912
20% Cut (but not 33%)	0.11	0.32	2912
33% Cut (but not 50%)	0.10	0.30	2912
50% Cut (but not 75%)	0.11	0.31	2912
75% Cut	0.09	0.29	2912
Not take 50-50 Gamble			
Doubling Inheritance or 10% Cut	0.51	0.50	2951
Take 50-50 Gamble			
Doubling Inheritance or			
10% Cut (but not 20%)	0.19	0.39	2951
20% Cut (but not 33%)	0.13	0.34	2951
33% Cut (but not 50%)	0.05	0.22	2951
50% Cut (but not 75%)	0.05	0.22	2951
75% Cut	0.07	0.25	2951
Panel D: Portfolio Choices	[1]	[2]	[3]
Has House	0.84	0.37	6460
Has Business	0.08	0.28	6460
Any Stocks	0.46	0.50	5450

Notes: This table reports means and standard deviations for additional variables used to investigate mechanisms underlying the estimated gene-wealth gradient. Each panel corresponds to an alternative mechanism. Mechanisms include Transfers (Panel A); Mortality (Panel B); Risk aversion (Panel C); Portfolio choices (Panel D); Beliefs and planning horizons (Panel E); and Defined-benefit pensions (Panel F). *This table continues onto the following page.*

Appendix Table S6: Summary Statistics: Mechanisms (continued)

	Mean	SD	N
Panel E: Beliefs and Planning Horizons	[1]	[2]	[3]
Prob: Stock Market Up			
Reported Probability	48.21	26.12	35842
Deviation from Objective	28.31	20.00	35842
Report 0%	0.05	0.22	35842
Report 50%	0.30	0.46	35842
Report 100%	0.04	0.19	35842
Prob: Major Depression			
Reported Probability	44.60	28.71	35912
Deviation from Objective	24.94	16.61	35912
Report 0%	0.07	0.26	35912
Report 50%	0.26	0.44	35912
Report 100%	0.06	0.24	35912
Prob: Double Digit Inflation			
Reported Probability	46.77	26.75	22604
Deviation from Objective	26.10	18.71	22604
Report 0%	0.06	0.23	22604
Report 50%	0.34	0.47	22604
Report 100%	0.07	0.26	22604
Planning Horizon:			
Less than 1 Year	0.13	0.34	27752
More than 1 Year	0.12	0.33	27752
More than a Few Years	0.30	0.46	27752
5-10 Years	0.34	0.47	27752
More than 10 Years	0.11	0.32	27752
Panel F: Pensions	[1]	[2]	[3]
Has DB Pension	0.57	0.49	5621
Pension Value (in $1000)	234.02	236.57	3226

Notes: This table reports means and standard deviations for additional variables used to investigate mechanisms underlying the estimated gene-wealth gradient. Each panel corresponds to an alternative mechanism. Mechanisms include Transfers (Panel A); Mortality (Panel B); Risk aversion (Panel C); Portfolio choices (Panel D); Beliefs and planning horizons (Panel E); and Defined-benefit pensions (Panel F).

B Additional Results

This appendix contains additional results referenced in the main text. Additional results are related to assortative mating, the relationship between the EA score and parental education and inheritances, and the relationship between beliefs, the financial planning horizon, wealth, and stock market participation.

B.1 Assortative Mating

Table S7 provides the evidence for the extent of assortative mating in our sample. We restrict attention to households in which both spouses have EA scores. First, we sort both males and females into quartiles, respectively, based on their individual EA scores. We then calculate the fraction of men in each male EA quartile within a given female EA quartile, and normalize so that the columns sum to one.[35] Panel A reports these distributions for individuals sorted by the raw, unadjusted value of their individual EA scores; Panel B reports distributions where individuals have been sorted based on the residual in a regression of their individual EA score on degree dummies and years of schooling. With perfect assortative mating, the matrices reported in Table S7 would be diagonal matrices, with 100% populating the diagonal entries and 0% populating the off-diagonal entries. Alternatively, random assignment would generate matrices with 25% for each entry.

We find some evidence of assortative mating, especially among the highest and lowest EA score quartiles. We find that 27.3% of women in the lowest individual EA score quartile are coupled with men in the lowest individual EA score quartile, compared to 26.9% coupled with men in the second quartile, 28.5% coupled with men in the third quartile, and 17.3% coupled with men in the fourth quartile. Entries in the fourth quartile of females' EA scores show similar patterns, with only 18.8% of the highest EA quartile women coupled with the highest EA-quartile men, compared to 33.5% coupled with the highest EA quartile males. Although we are able to reject the random-assignment null hypothesis that all entries are equal to 25% ($p < 0.001$), the degree of assortative mating appears modest relative to the counterfactual of perfect sorting. Indeed, while the within-couple correlation of years of schooling is 0.52, the within-couple correlation of individual EA scores is only 0.14.

[35]This exercise closely follows Charles, Hurst, and Killewald (2013) (see their Table 5 on p. 61), who examine assortative mating on parents' wealth.

B.2 Transfers and Parental Education

In Table S8, we relate the EA score to inheritances. All regressions include our standard controls and full education controls, unless otherwise noted. In Column [1] of Table S8, we estimate a cross-sectional regression where the dependent variable is an indicator variable equal to one if the household has ever received an inheritance over the span of the sample. In Column [2] we estimate a cross-sectional regression where the dependent variable is the log of the real dollar value of all inheritances received over the sample. Because the log of total inheritances is defined only for values greater than zero, this specification is equivalent to a regression of inheritance values conditional on receiving an inheritance. We find no relationship between the EA score and either the probability of receiving an inheritance or the size of inheritance wealth conditional on receiving an inheritance.

Next, we regress different measures of parental education on the household's average EA score. In Column [3], the dependent variable is the average education of the fathers of both household members, and we include our standard controls but no measures of respondent education. Column [4] presents the same specification but with the average of mothers' education as the dependent variable. Results suggest the education of both parents are strongly related to the household average EA score. In Columns [5] and [6], we investigate whether the relationship between parental education and the EA score is entirely explained by household members' own education. In Column [5] the dependent variable is again average fathers' education, but we now include the full set of household education controls. Column [6] reports analogous coefficients with average mothers' education as the dependent variable. The estimated coefficients on the EA score are reduced dramatically but remain statistically significant for fathers' education (and marginally significant for mothers' education), which indicates that household environments and other investments could play a role in wealth accumulation beyond just educational attainment.

B.3 Macroeconomic Beliefs and Household Behavior

The results in Table 10 suggest that individuals with lower genetic scores are more likely to report beliefs that are at odds with objective probabilities and are more likely to report "extreme" beliefs. It is possible, however, that these reported beliefs are not related to individual behavior in a meaningful way, making these results interesting but not particularly useful for understanding the potential underlying mechanisms linking the EA score to financial decisions. This would be the case if either the HRS expectations questions do a poor job of eliciting true beliefs about these economic events, or if the events themselves were not relevant for the household's choice problem. Whether a longer financial planning horizon is associated with greater wealth is a similarly empirical question.

Table S9 shows that some of these elicited measures do indeed predict relevant behaviors such as stock market participation, and are associated with wealth. Column [1] regresses log wealth on indicators for whether the household ever reported an extreme belief for any of the three macroeconomic expectations (stock market appreciation, severe recession, or double-digit inflation), and indicators for which financial planning horizon households report. Both the financial planning horizon and stock market beliefs are related to accumulated wealth. Interestingly, excessive optimism about the stock market is actually associated with *greater* wealth, likely due to an increase in participation. This suggests that the direction of incorrect beliefs is important for their overall impact on wealth. Column [2] repeats this exercise but includes the EA score as an additional control. The inclusion of the belief and planning horizon variables reduces the coefficient on the EA score from 0.047 to 0.038.

In Columns [3] and [4] we repeat the specifications in Columns [1] and [2], but replace the log wealth with stock market participation as the dependent variable. Consistent with economic theory, longer planning horizons are associated with greater stock market participation. Reassuringly, extreme optimistic beliefs are also positively associated with stock market participation, whereas extreme pessimistic beliefs are negatively (but statistically insignificantly) related. Column [4] also shows that the positive relationship between the EA score and stock ownership documented in Table 9 remains after inclusion of belief and planning horizon controls.

Appendix Table S7: EA Score and Assortative Mating

	Panel A: Unadjusted means (N=939)				**Panel B:** Adjusted for degree and years of education (N=939)			
	Female EA Quartile				Female EA Quartile			
Male EA Quartile	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
	[1]	[2]	[3]	[4]	[1]	[2]	[3]	[4]
Q1	27.3	27.4	20.3	18.8	25.4	21.6	25.4	21.9
Q2	26.9	21.4	26.3	25.9	29.0	23.4	27.2	25.3
Q3	28.5	27.4	22.8	21.9	24.6	28.8	24.6	23.6
Q4	17.3	23.9	30.6	33.5	21.0	26.1	22.8	29.1

Notes: This table reports the distribution of the male household member's EA score conditional on the quartile of the female household member's EA score for all coupled households with non-missing EA scores for both members. For each panel, each row-column entry reports the probability that a female with an EA score in the quartile corresponding to the column is coupled with a male whose EA score is in the quartile corresponding to the row. The column probabilities sum to 100 percent. Panel A presents these statistics based on unconditional individual EA scores. Panel B presents the same statistics based on the residual EA score obtained from a regression of the individual EA score on years of education and indicators for highest degree attained.

Appendix Table S8: Transfers: Inheritances and Parental Education

Dep. Var:	**Receive Inheritance**	**Inheritance Amount**	**Fathers' Educ.**	**Mothers' Educ.**	**Fathers' Educ.**	**Mothers' Educ.**
	[1]	[2]	[3]	[4]	[5]	[6]
EA Score	0.011	0.097	0.777***	0.548***	0.277***	0.111*
	(0.012)	(0.071)	(0.069)	(0.062)	(0.076)	(0.065)
Obs.	2556	1054	2294	2345	2294	2345
R^2	0.260	0.411	0.200	0.178	0.408	0.403
Standard Controls	X	X	X	X	X	X
Principal Comp.	X	X	X	X	X	X
Full Educ. Controls	X	X			X	X

Notes: This table presents estimates from regressions of inheritance and parental education variables on the average household EA score and various controls. In Column [1], the dependent variable is a binary that takes a value of 1 if the household ever receives an inheritance in the sample. In Column [2], the dependent variable is the log of the total real inheritance amount that the household receives over the course of the sample, conditional on having received an inheritance. In Column [3], the dependent variable is average years of fathers' education (averaging over household members). Column [4] repeats this exercise for average years of mothers' education. Columns [5] and [6] repeat the analysis in Columns [3] and [4], but now include controls for education of household members. Significance stars ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. Standard errors are clustered at the family level.

Appendix Table S9: Beliefs, Stock Market Participation and Wealth

Dep. Var:	**Log Wealth**	**Log Wealth**	**Own Stocks**	**Own Stocks**
	[1]	[2]	[3]	[4]
EA Score		0.038*		0.044***
		(0.021)		(0.011)
Ever Prob. Stock Mkt. Up: 0%	-0.020	-0.020	-0.044	-0.044
	(0.053)	(0.053)	(0.028)	(0.028)
Ever Prob. Stock Mkt. Up: 100%	0.169***	0.169***	0.069***	0.068***
Ever Prob. Recession: 0%	-0.000	0.000	-0.003	-0.003
	(0.037)	(0.037)	(0.021)	(0.021)
Ever Prob. Recession: 100%	0.123*	0.127*	0.011	0.015
Ever Prob. DD Inflation: 0%	-0.029	-0.026	-0.015	-0.011
	(0.045)	(0.045)	(0.025)	(0.025)
Ever Prob. DD Inflation: 100%	-0.095	-0.087	-0.017	-0.007
Min PH More than 1 Year	0.234***	0.234***	0.068***	0.066***
	(0.043)	(0.043)	(0.024)	(0.023)
Min PH More than a Few Years	0.277***	0.273***	0.078***	0.071***
	(0.040)	(0.040)	(0.026)	(0.026)
Min PH 5-10 Years	0.589***	0.588***	0.183***	0.177***
	(0.085)	(0.085)	(0.045)	(0.045)
Min PH More than 10 Years	0.761***	0.771***	0.373***	0.371***
	(0.273)	(0.278)	(0.117)	(0.120)
Obs.	5158	5158	5285	5285
R^2	0.506	0.506	0.367	0.372
Standard Controls	X	X	X	X
Principal Comp.	X	X	X	X
Full Educ. Controls	X	X	X	X
Log Income	X	X	X	X

Notes: This table presents estimates from regressions of log household wealth on measures of household subjective beliefs, planning horizons, the average household EA score, and various controls. The belief and planning horizon measures are time-invariant variables constructed from the panel of household responses. Specifically, for each of the three macroeconomic events examined in Section 5.5, we construct separate dummy variables indicating whether any household member ever reports a subjective probability of 0 percent or 100 percent, respectively. For each event, we also include the maximum deviation ever observed between a household member's subjective belief and our benchmark objective probability. We also include a series of dummy variables indicating the minimum financial planning horizon held by any household member. Significance stars ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. Standard errors are clustered at the family level.

C Robustness

This appendix contains robustness tests that are largely based on the main associations reported in Table 4. We examine robustness to the application of sampling weights, as well as alternate sample definitions, measurements of household EA scores, income specifications, wealth definitions, and control sets.

C.1 Household Structure and EA Score

This section assesses the robustness of the main results presented in Table 4 to changes in the sample definition, as well as changes in how we aggregate the EA score within two-person households. In Table S10, we address four possible selection issues that may affect the main results. In Columns [1] and [2], we repeat specifications from Columns [5] and [7] in Table 4, but apply the HRS supplied sample weights. In Columns [3] and [4] we address potential selection bias from mortality including only one observation per household; this may be important if wealthier people with higher EA scores live longer and are therefore disproportionately represented in a full panel. In Columns [5] and [6], we restrict the sample to only "coupled" households, in which the household has two members in at least one sample wave. We note that this sample may include household-year observations after a spouse has died. The results in Columns [1]-[6] all continue to demonstrate a economically large and statistically significant association between the EA score and wealth. Finally, in Columns [7] and [8], we evaluate whether the maximum or minimum EA score is ultimately driving the main association. In these specifications, we restrict the sample to households with non-missing EA scores for both members. Estimates in these specifications are quite imprecise, and in both regressions we fail to reject the null hypothesis that the coefficients on both scores are the same. The lack of precision here is likely driven by the fact that the sample size is reduced dramatically when restricting to coupled households with two non-missing scores.

C.2 Alternate Definitions of Income

The income data described in Section 3.2 are based on data from the Social Security Administration (SSA). The SSA data contain earnings information for most or all of respondents' working lives. This offers a clear advantage relative to the self-reported income measures in the HRS, which only cover older ages. However, an important limitation of the SSA data is that they are top-coded at the taxable maximum amount for Social Security payroll taxes.[36] Panel B of Table S3 presents summary statistics relevant for the SSA income measure and top-coding. Across households, the average number of person-years with top-coded income observations is 12.67 in our sample. Less than one-third (27%) of households are never top-coded. To partially correct for top-coding, we use Current Population Survey (CPS) data to calculate mean income for people earning at least the top-coded level in each year over the period 1961-2010. We then replace the top coded amount in the SSA data with the conditional mean from the CPS data for each of these years.[37]

Table S11 presents estimates from specifications with a variety of alternative controls for lifetime household income. All specifications include the same set of controls as Column [7] in Table 4. Column [1] of S11 measures household income using the log of average household income observed within the HRS sample. Column [2] includes the log of total household income from the SSA (our standard measure), but also includes a complete set of dummy variables for each possible number of top-coded years in the SSA earnings data. Column [3] is the same as Column [2], but further includes dummy variables for each quintile of the distribution of SSA earnings across households. Column [4] controls for lifetime income using a quintic polynomial of the log of total household income from the SSA. Column [5] is the same as our basic specification (Column [7] in Table 4), but drops households in which any member is ever observed in two separate households (e.g., households that split due to a divorce). This specification addresses concerns that lifetime income might be divided across households that separate. Finally, Column [6] controls for income using the log of the average of SSA earnings over the household's 35 highest earning years. Across all of these specifications, we robustly estimate an economically large statistically significant coefficient on the EA score. Estimates of the coefficient on the EA score fall in a fairly narrow range of 0.041-0.061.

C.3 Alternative Definitions of Wealth

In this section, we repeat the analysis in Table 4 using different measures of household wealth. In Column [1] of Table S12, we use the measure of wealth provided by RAND, which does not include the present discounted value of retirement income or the retirement account balances

[36] This taxable maximum has changed substantially over time. In some years, especially in the 1960s and 1970s, a substantial portion of households fall into this category since the maximum was fairly low. For example, in 1965 the maximum was $4,800 (which is about $38,000 in 2018 dollars).

[37] For example, if an individual earned $10,000 (nominal) in 1965, we would observe a top-coded income amount of $4,800 in the SSA file. The mean CPS income for those earning at least $4,800 in 1965 is $8,103 so we would replace this individuals' income (any 1965 SSA amount of at least $4,800) with $8,103, which is approximately $56,096 in 2010 dollars.

still held with employers. In Column [2], we use the measure of wealth used in our main analysis but subtract the net value of housing. In Column [3], we again use our main wealth measure, but subtract the present discounted value of defined-benefit pension, annuity, and social security income. In Column [4], we subtract both housing and retirement-income wealth. Finally, in Column [5], we subtract the value of privately held businesses. In all specifications the key patterns from our main results remain largely unchanged.

C.4 Sample Selection

Table S13 presents estimates of our basic results from Table 4 using four different possible sample definitions. For each alternate sample, we present two specifications corresponding to Columns [5] and [7] in Table 4. Columns [1]-[2] of S13 present estimates from our baseline sample of retired households with members aged 65-75, which are reproduced from Table 4. To understand whether these results are affected by the retirement or age restrictions on this sample, we consider three other sample definitions. Columns [3]-[4] present estimates from a sample of retired households with members aged 55-85. Columns [5]-[6] present estimates from a sample of all households regardless of retirement status with members aged 50-75, while the sample used in Columns [7]-[8] includes all households with members aged ≤ 85. Across all of these samples, we consistently estimate economically large and statistically significant coefficients on the EA score in the range 0.047-0.084.

C.5 Alternative Scores

In Table S14, we examine whether the main association established in Table 4 is affected by using alternate polygenic scores for educational attainment. For each alternative score, we construct a household average and replicate Column [7] of Table 4. The score used in Column [1] is based on the Lee et al. (2018) GWAS (as is the main score used in our analysis). Since Lee et al. (2018) is the third in a series of GWAS on educational attainment by the same consortium, it is referred to as the EA3 score. The version of the EA3 score featured in Column [1] is not constructed with the LDpred method used to construct our primary score. Rather, this version is simply the sum of all SNPs weighted by their GWAS coefficients, and was released by the HRS for all genotyped waves. Consequently, this score is available for more households than the LDpred EA3 score, which was only calculated for individuals genotyped in the 2006 and 2008 waves. In Column [1] we use this non-LDpred score, but restrict the sample to households included in our main sample. We estimate a coefficient on the EA3 score of 0.038 in this specification. In Column [2], we use this score for all genotyped households (including individuals genotyped in the 2010 and 2012 waves), and estimate a coefficient of 0.044. The stability of the coefficient across these specifications suggests that our main association is not greatly affected by the expansion of the genotyped subsample over time.

Columns [3]-[4] estimate specifications based on a score built from the Okbay et al. (2016) GWAS results (referred to as EA2, since it was the second education GWAS by this consortium), which featured a discovery sample size of $N = 293,723$. The score used in these specifications is the all-SNP (non-LDpred) score released by the HRS. In column [3] we restrict the sample to households that are included in our main sample, while column [4] expands the sample to include household-year observations with individuals genotyped in the 2010 and 2012 waves. The coefficients estimated in these specifications are similar to the coefficients estimated in Columns [1]-[2] using the EA3 scores. Finally, Columns [5]-[6] present results with the score based on the EA1 GWAS results from Rietveld et al. (2013), which featured a sample size of $N = 126,559$. Column [5] presents results for an LDpred score, while column [6] presents results from a score that sums all SNPs weighted by their GWAS association sizes. Both scores exhibit a weak, statistically insignificant association with log households wealth.

C.6 Alternative Control Sets

In this section, we examine the robustness of the main results in Table 4 to the inclusion of additional controls. In Columns [1]-[2] of Panel A in Table S15, we add the average household cognitive test score to our two baseline specifications (Columns [5] and [7] in Table 4). If the gene-wealth gradient in part arises from facility with complex decisions, a cognitive test score may explain much of the association captured by the EA score. However, the cognitive test score in the HRS is designed to capture cognitive decline and is only moderately correlated with the EA score. The average household test score is 23.89 (out of a total of 35) with averages for females and males of 24.40 and 23.22, respectively. Inclusion of the average household cognitive test score does not affect our main results. In Columns [3]-[4] of Panel A in Table S15, we include the maximum number of children associated with a household member. Higher EA score individuals may have more wealth at retirement due to having fewer children. The average number of children in the full analytical sample is 3.70, and households with higher average EA scores have fewer children. For individuals with EA scores in the first quartile, the average number of children in their household is 3.90 (again using the maximum observed for the household). For individuals with EA scores in the fourth quartile, the average is 3.34. However, inclusion of number of children leaves results unchanged.

In Panel B of Table S15, we include controls for years since retirement and years since the death of a household member. Columns [1]-[2] modify our baseline specifications by adding separate sets of dummy variables for the number of years that the male and female household members have been retired, respectively. We interact these variables with dummies for male-only and female-only households, respectively. If higher EA score individuals retire later than respondents with lower scores, this could explain greater wealth accumulation. The coefficient in column [2] decreases some, and becomes marginally statistically insignificant at the 10% level (p-value of 0.108). The death of a household member may be associated with a spike in expenses related to end-of-life care, followed by a systematic change in household consumption and decision-making. Therefore, in Columns [3]-[4], we control for the death of a household member by adding a full set of dummies for the number of years since the male and female household member has died, respectively. We also add an indicator for a coupled household that only has one member in it during a given year. The resulting coefficient estimates are again similar to our baseline estimates. Finally, in Panel C, we estimate specifications in which we simultaneously include all of the additional controls from Panels A and B. Adding all of these controls reduces the coefficient on the EA score, and in column [2] again becomes statistically insignificant.

Appendix Table S10: EA Score and Household Wealth: Robustness to Alternative Definitions of Households and EA Score Aggregation

Dep Var: Log Wealth	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
EA Score	0.069***	0.053**	0.081***	0.065**	0.103***	0.076***		
	(0.023)	(0.021)	(0.027)	(0.027)	(0.024)	(0.023)		
Max HH EA Score							0.052	0.034
							(0.034)	(0.034)
Min HH EA Score							0.052	0.051
							(0.036)	(0.035)
Log Income		0.265***		0.259***		0.228***		0.209***
		(0.038)		(0.046)		(0.034)		(0.056)
Obs.	5598	5286	2556	2371	3930	3723	1927	1870
R^2	0.429	0.473	0.454	0.496	0.409	0.450	0.474	0.506
Sampling Weights	X	X						
First Year Only			X	X				
Coupled HH Only					X	X		
Standard Controls	X	X	X	X	X	X	X	X
Principal Comp.	X	X	X	X	X	X	X	X
Years of Educ.	X	X	X	X	X	X	X	X
Full Educ. Controls	X	X	X	X	X	X	X	X

Notes: This table shows regression coefficients where the outcome variable is log household wealth with various control sets and sample restrictions indicated above. Significance stars ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. Standard errors are clustered at the family level.

Appendix Table S11: EA Score and Household Wealth: Robustness to Alternative Income Controls

Dep. Var: Log Wealth	[1]	[2]	[3]	[4]	[5]	[6]
EA Score	0.061***	0.041*	0.044**	0.047**	0.047**	0.051**
	(0.023)	(0.022)	(0.022)	(0.021)	(0.023)	(0.022)
Log Avg. Annual Income (HRS)	0.267***					
	(0.030)					
Log Total Income (SSA)		0.194***	0.234***	26.898	0.277***	
		(0.055)	(0.087)	(68.995)	(0.041)	
Log Total Income (SSA)^2				-4.246		
				(12.639)		
Log Total Income (SSA)^3				0.340		
				(1.120)		
Log Total Income (SSA)^4				-0.014		
				(0.048)		
Log Total Income (SSA)^5				0.000		
				(0.001)		
Log Avg. Income (Top 35)						0.260***
						(0.037)
Obs.	3993	5308	5290	5308	4895	5383
R^2	0.490	0.495	0.496	0.500	0.490	0.475
Standard Controls	X	X	X	X	X	X
Principal Comp.	X	X	X	X	X	X
Full Educ. Controls	X	X	X	X	X	X

Notes: This table shows regression coefficients where the outcome variable is log household wealth, which is regressed on average household EA score. Each column represents an alternate version of the specification in Column [7] of Table 4 with an alternate measure of household income. In Column [1], we replace our main income measure with the log of average household income for non-retired years observed in the HRS. In Column [2], we control for the number of top-coded years observed in the household's income history (separate dummy variables for each possible number of top-coded years) in addition to our main SSA measure of lifetime household income. In Column [3], we add separate dummy variables for each quintile of household income to the specification in Column [2]. In Column [4], we control for income using a quintic in the SSA log income measure. In Column [5], we use our standard SSA income measure, but restrict to households where members are never observed in multiple households. In Column [6], we control for the log of the average of SSA income in the household's highest 35 35 years of earnings. Significance stars ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. Standard errors are clustered at the family level.

Appendix Table S12: EA Score and Household Wealth: Robustness to Alternative Wealth Measures

Dep. Var: Log Wealth	RAND Wealth	Subtract Housing Wealth	Subtract Pension Wealth	Subtract Housing and Pension Wealth	Subtract Business Wealth
EA Score	0.107**	0.040*	0.126***	0.180***	0.046**
	(0.043)	(0.021)	(0.047)	(0.056)	(0.021)
Log Income	0.260***	0.285***	0.339***	0.474***	0.268***
	(0.053)	(0.037)	(0.064)	(0.069)	(0.037)
Obs.	6124	5289	4990	4657	5308
R^2	0.414	0.476	0.407	0.416	0.482
Standard Controls	X	X	X	X	X
Principal Comp.	X	X	X	X	X
Years of Educ.	X	X	X	X	X
Full Educ. Controls	X	X	X	X	X

Notes: This table shows regression coefficients where the outcome variables are different measures of log household wealth regressed onto average household EA score and various controls. Each column corresponds to the specification in Column [7] of Table 4 from the main text. Significance stars ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. Standard errors are clustered at the family level.

Appendix Table S13: EA Score and Household Wealth: Robustness to Sample Selection

Dep. Var: Log Wealth	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
EA Score	0.070***	0.047**	0.076***	0.060***	0.079***	0.057***	0.084***	0.067***
	(0.023)	(0.022)	(0.017)	(0.017)	(0.018)	(0.018)	(0.015)	(0.015)
Log Income		0.263***		0.217***		0.284***		0.233***
		(0.038)		(0.027)		(0.029)		(0.023)
Obs.	5621	5308	13708	12628	18925	17563	25815	23720
R^2	0.435	0.479	0.413	0.446	0.358	0.387	0.362	0.389
Standard Controls	X	X	X	X	X	X	X	X
Principal Comp.	X	X	X	X	X	X	X	X
Full Educ. Controls	X	X	X	X	X	X	X	X

Notes: This table shows regression coefficients in specifications that correspond to Columns [5] and [7] in Table 4, for different sample definitions. Columns [1]-[2] include our baseline sample of retired households with members aged 65-75, which are reproduced from Table 4. Columns [3]-[4] present estimates from a sample of retired households with members aged 55-85. Columns [5]-[6] present estimates from a sample of all households regardless of retirement status with members aged 50-75. Columns [7]-[8] include all households with members aged ≤ 85. Standard errors are clustered at the family level.

Appendix Table S14: EA Score and Household Wealth: Robustness to Alternative Versions of the EA Score

Dep. Var: Log Wealth	[1]	[2]	[3]	[4]	[5]	[6]
EA3 Score no LDpred	0.038*	0.044**				
	(0.022)	(0.021)				
EA2 Score no LDpred			0.037*	0.040**		
			(0.021)	(0.020)		
EA1 LDpred					0.007	
					(0.020)	
EA1 no LDpred						0.008
						(0.020)
Obs.	5297	5964	5297	5964	5308	5308
R^2	0.479	0.474	0.479	0.474	0.478	0.478
Standard Controls	X	X	X	X	X	X
Principal Comp.	X	X	X	X	X	X
Full Educ. Controls	X	X	X	X	X	X
Log Income	X	X	X	X	X	X

Notes: This table shows regression coefficients where the outcome variable is log household wealth. In each column, we replicate Column [7] of Table 4 from the main text, but use a different version of the EA score. In Column [1], the polygenic score is constructed using all SNPs without the LDpred method based on the GWAS results of Lee et al. (2018), and the sample is restricted to include only households in our main analytical sample. Column [2] is the same as Column [1], but now expands the sample to include individuals genotyped in the 2010 and 2012 waves. In Columns[3]-[4], we use the all SNPs score based on results from a GWAS of $N = 293,723$ individuals reported in Okbay et al. (2016), which is publicly available from the Health and Retirement Study. Column [3] restricts the sample to individuals with non-missing values of the main score used in this paper, while Column [4] adds more observations by including individuals genotyped in 2010 and 2012. Columns [5]-[6] report results for scores based on the GWAS of $N = 126,559$ individuals from Rietveld et al. (2013). The score in Column [5] is based on the LDpred method, while the score in Column [6] is not.

Appendix Table S15: EA Score and Household Wealth: Robustness to Alternative Control Sets

Panel A: Dep. Var: Log Wealth	[1]	[2]	[3]	[4]
EA Score	0.058***	0.039*	0.067***	0.046**
	(0.022)	(0.021)	(0.023)	(0.022)
Avg. HH Cog. Test Score	0.032***	0.024***		
	(0.004)	(0.004)		
Max No. Children in HH			-0.041***	-0.043***
			(0.010)	(0.009)
Obs.	5495	5191	5614	5305
R^2	0.454	0.495	0.442	0.486
Log Income		X		X
Panel B: Dep. Var: Log Wealth	[1]	[2]	[3]	[4]
EA Score	0.055**	0.036	0.064***	0.041*
	(0.023)	(0.023)	(0.022)	(0.021)
Obs.	5295	5017	5621	5308
R^2	0.493	0.532	0.452	0.497
Log Income		X		X
Retirement Controls	X	X		
Mortality Controls			X	X
Panel C: Dep. Var: Log Wealth	[1]	[2]		
EA Score	0.042*	0.027		
	(0.022)	(0.021)		
Avg. HH Cog. Test Score	0.029***	0.021***		
	(0.004)	(0.004)		
Max No. Children in HH	-0.037***	-0.038***		
	(0.008)	(0.008)		
Obs.	5189	4920		
R^2	0.526	0.562		
Log Income		X		
Retirement Controls	X	X		
Mortality Controls	X	X		

Notes: This table shows regression coefficients where the outcome variable is log household wealth. Pairs of Columns for each control set correspond to those in Columns [5] and [7] of Table 4 from the main text. In Panel A, we include controls for the average cognition score in the household and the maximum number of children born to a household member. In Panel B, we add controls for years since retirement and death of a household member. In Panel C, we add all of the controls used in Panels A and B. Significance stars ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. Standard errors are clustered at the family level.