Genetic Ability, Wealth, and Financial Decision-Making*

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Abstract: Recent advances in behavioral genetics have led to the discovery of genetic markers linked to a variety of economically relevant choices, including education. These markers can be aggregated to form *polygenic scores*: indices that summarize genetic endowments associated with particular outcomes. We demonstrate that a polygenic score for educational attainment predicts household wealth independently of education in the Health and Retirement Study. A substantial portion of this association cannot be explained by income flows, inheritances, business ownership, and other standard channels. Stock market participation does play an important role, which suggests financial sophistication may be a relevant mechanism. We find that individuals with higher genetic scores exhibit better financial literacy and are less prone to reporting incorrect or "extreme" beliefs (e.g., reporting probabilities of 0% or 100%). These extreme beliefs are not due solely to noise or respondent confusion. For example, households that report extreme optimism about the stock market are substantially more likely than others to invest in stocks. High score individuals also report longer financial planning horizons. These results indicate that genetic factors associated with human capital accumulation predict wealth disparities not only through education and income flows, but also through the ability to process information and make sound financial decisions. Consistent with this interpretation, we find the association between the genetic score and wealth is substantially weaker among households that receive defined benefit pension income. Our findings suggest that increased autonomy over financial decisions may benefit some while harming others.

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1 Introduction

Wealth inequality in the United States and many other countries is large and growing (Saez and Zucman, 2014; Jones, 2015). An extensive literature attempts to explain wealth inequality through variation in the earnings process, entrepreneurial talent, bequests, risk aversion and time-discounting. While these factors can generate a skewed wealth distribution, they fail to reproduce other key empirical features including the thickness of the tail.[1]

A new wave of theoretical work 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).[2] Despite the theoretical and empirical importance of this phenomenon, little is known about what drives such persistence. However, policy responses to wealth inequality are likely to have different effects depending on the mechanisms through which persistent heterogeneity operates — for example, whether this heterogeneity comes from variation in preferences (e.g. risk aversion) or variation in skills (e.g. financial decision-making).

In this paper, we identify a biological basis for heterogeneity in wealth: genetic endowments related to human capital accumulation. In particular, we show that the same observed genetic markers that predict educational attainment also predict household wealth in the Health and Retirement Study (HRS). Importantly, this relationship is not entirely explained by earnings or other income flows. Rather, the estimated association between genes and wealth is economically large and statistically significant after controlling for education, earnings, inheritances, business ownership, and a host of other factors. By observing these genetic variants, we can more directly assess the potential mechanisms through which they operate and understand how they interact with economic environments. We provide novel evidence that the genetic endowments we study are linked to financial decision-making (in particular stock market participation), financial literacy, planning horizons, and probabilistic thinking.

[1]Some models can match the thickness of the tail, but only under implausible assumptions about the level of heterogeneity in the earnings process. For example, Kindermann and Krueger (2014) require the top 0.25% of earners to earn 400-600 times more than the median earner. Empirically, this number is closer to 33.

[2]In an earlier contribution, Yitzhaki (1987) examines the relationship between income and returns, which is consistent with the idea that wealthier individuals face higher returns since income can generate higher wealth.

While we do not observe returns directly, our results provide a possible genetic micro-foundation for the persistent differences in returns to wealth needed to match existing wealth distributions. Because genetic endowments are heritable, this suggests another source for the well-documented inter-generational persistence of wealth (Charles and Hurst, 2003).[3] Moreover, because financial decisions and beliefs about the macroeconomy play an important role in explaining the genetic gradient in wealth, relatively straightforward policy tools such as stronger public pension schemes may help to reduce wealth inequality and poverty among the elderly 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).

The genetic endowments that we study come from recent advances in behavioral genetics that identify specific genetic markers that predict educational attainment. Results from the state of the art in this literature (Okbay et al., 2016) allow for the construction of a *polygenic score* — an index of these genetic markers — that robustly predicts education, including in the HRS (Papageorge and Thom, 2016). The use of genetic information offers a new approach to studying the nature of ability endowments. Unlike traditional proxies for ability such as cognitive test sores (e.g. IQ), genetic measures are *predetermined* if not exogenous, and are not causally affected by endogenous investments. Using molecular genetic data to directly observe these endowments greatly eases the process of understanding the mechanisms through which they operate, and the ways in which they interact with policies and macroeconomic conditions.

We establish a robust relationship between the polygenic score and wealth in retirement. A one-standard-deviation increase in the score is associated with a 23 percent increase in household wealth (approximately $120,453 in levels). Education accounts for a little more than half of this association. Labor market earnings, an important source of differences in household wealth, explains at most a modest portion of this relationship.[4] Inheritances, which could capture how individuals with higher polygenic scores have parents who are more highly educated and therefore wealthier, and business ownership are similarly incapable of explaining much of this relationship. Despite these controls, the polygenic score continues to exhibit a strong and economically large relationship with household wealth.

Next, we test whether these genetic factors relate to investment decisions. A classic example of such a decision is stock market participation (Vissing-Jørgensen, 2002). We demonstrate that the polygenic score predicts stock market participation even after we have

[3]On the importance of inter-generational transmission of economic outcomes, a key contribution is Black, Devereux, and Salvanes (2005).

[4]Though higher lifetime-income households save more (Dynan, Skinner, and Zeldes, 2004), as Venti and Wise (1998) demonstrate using HRS data, lifetime income does not fully explain wealth inequality.

controlled for education, wealth, and income, and that stock ownership plays an important role in mediating the relationship between genetic endowments and wealth. An obvious explanation for this finding is that the polygenic score predicts differences in risk preferences, but measures of risk aversion available in the HRS do not appear to explain this relationship.[5] Because stock market participation affects returns to wealth, these results may link the genetic endowments captured by the polygenic score to the persistent heterogeneity in returns described in Benhabib, Bisin, and Zhu (2011).

Our next set of results exploits rich data on factors that may affect financial decision-making. Lusardi, Michaud, and Mitchell (2017) demonstrate that heterogeneity in returns on savings, which are plausibly determined by financial knowledge, can explain a substantial proportion of wealth inequality. Another set of papers demonstrates links between subjective beliefs and investment behaviors that impact household wealth (Dominitz and Manski, 2007; Lillard and Willis, 2001).[6] We show that a higher polygenic score predicts greater financial literacy as well as more objectively correct expectations about macroeconomic events. Lower polygenic scores are associated with beliefs about these events that are heaped on probabilities of 0% or 100% (a phenomenon we refer to as "extreme beliefs"). These extreme beliefs may reflect difficulty with probabilistic thinking, which could lead to sub-optimal decisions in uncertain environments (Kahneman and Tversky, 1972). Importantly, extreme beliefs do not appear to solely reflect respondent confusion or measurement error; households that report extreme beliefs make choices that are consistent with their beliefs. For example, households that report a 100% probability of a stock market increase over the following year are 20 percentage points more likely to invest in stocks than those that report a 0% probability.

These results suggest that individuals with higher polygenic scores are better able to navigate complex financial decisions. Consistent with this interpretation, we find that a higher polygenic score predicts a longer financial planning horizon. Solving inter-temporal choice problems is often challenging; high score individuals may find it easier to assess the impact of current choices on long term outcomes. Alternatively, a longer planning horizon could reflect greater patience. However, we find little variation in elicited discount factors across planning horizons. Collectively, the financial planning horizon and various measures

[5] Previous research suggests that risk aversion has a genetic basis (Cesarini et al., 2009). Unfortunately, a measure of risk aversion is available only for a subsample of individuals in the HRS. Controlling for this measure does not substantially attenuate the genetic gradient, but we may be under-powered to detect meaningful differences.

[6] 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).

of expectations account for a quarter of the relationship that remains between the polygenic score and wealth after controlling for labor income, inheritances, and business ownership.

If genetic ability affects wealth through the quality of financial decision-making, policies that grant individuals greater discretion in how they manage their finances should exacerbate ability-based inequality. We test this hypothesis by evaluating the extent to which defined benefit pension income mitigates the importance of genetic ability for wealth in retirement. 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 due to ability in financial decision-making. We find that the gene-wealth gradient is nearly three times as large for households who do not participate in defined benefit pension plans. This not only offers compelling support for our interpretation of the mechanisms linking the polygenic score to wealth, but also highlights a potentially important policy consideration. While programs such as 401(k) plans afford individuals greater freedom in planning for retirement, they may also reduce the welfare of individuals who are less capable of managing complex financial choices.

Our analysis both complements and contrasts with the findings of Cronqvist and Siegel (2015), who use twins data to study a genetic basis for *savings* behavior. They conclude that genetic factors related to savings and wealth may operate through time preference and self control because of genetic correlations between savings, smoking, and obesity. Though our results provide further evidence of a genetic basis for heterogeneity in wealth, we appear to identify distinct mechanisms. To highlight this point, we consider additional polygenic scores developed to predict BMI and smoking (cigarettes per day). We find that these three scores are not highly correlated and all three independently predict wealth.[7] However, we do not find any robust associations between the scores for BMI or smoking and expectations. Taken together, these results suggest that the genetic endowments linked to education, which are the primary focus of our study, are related to wealth through mechanisms that are independent of saving behavior.

Finally, we test whether childhood circumstances moderate the relationship between the polygenic score for education and the accuracy of macroeconomic expectations. Although defined benefit pensions appear to mitigate the consequences of poor-decision making, an alternate policy approach would focus on improving financial decision-making. For example, greater resources might allow households with low socioeconomic status (SES) to make human capital investments that improve financial skills. Measures of childhood SES have previously been shown to moderate the relationship between these genetic endowments and

[7] Indeed, this cross-validation demonstrates that twin studies and studies using polygenic scores yield similar patterns.

high school completion in the HRS (Papageorge and Thom, 2016). However, in our analysis we find that SES does not play such a moderating role for the accuracy of subjective expectations. We note, of course, that much more work is needed to determine whether interventions targeted specifically at financial decision-making could be useful in addressing the genetic gradient in wealth.

By linking genetic endowments to economic behavior and outcomes, our study contributes to an existing literature that focuses on proxies for ability, such as cognitive test scores. For example, Lillard and Willis (2001) study cognition and wealth, highlighting the importance of probabilistic thinking, and Grinblatt, Keloharju, and Linnainmaa (2011) and Grinblatt et al. (2015) link IQ to stock market participation and mutual fund choice. However, because parental investments can affect cognitive test scores, interpreting associations between such test scores and wealth is difficult. The existing work on genetics and financial behavior typically uses twins-studies rather than observations of specific genetic markers. Twins studies have shown that genetics play a non-trivial role in explaining saving behavior and portfolio choices (Cronqvist and Siegel, 2014, 2015; Cesarini et al., 2010).[8] However, it is generally difficult to learn about how specific genetic factors operate using twins data. For one, twins studies do not identify which particular markers matter for various economic decisions, which limits analysis of their function to variance decompositions related to mechanisms contained in existing twins data sets. Moreover, while testing hypotheses about specific mechanisms is conceptually possible using information on twins, in practice it requires large amounts of data to permit stratification by each potential mediating factor.[9] The development of polygenic scores helps to overcome these difficulties.

The remainder of this paper is organized as follows. Section 2 provides some background on the genetic index used in this paper. Section 3 introduces the data and provides details on the construction of wealth measures. Section 4 studies the relationship between the polygenic score and wealth. Section 5 analyzes the polygenic score, financial decision-making, economic expectations, planning horizons, and the effect of defined benefit plan participation. Section 5 end by discussing some policy implications of our results. Section 6 concludes.

[8]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 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).

[9]Variance decomposition exercises such as twins studies treat genes as unobserved factors. Learning about interactions between observed and unobserved factors is generally difficult and relies on modeling assumptions.

2 Genetic Data and GWAS

We use a polygenic score that predicts educational attainment. Since economists are only just beginning to use genetic data, we first provide a brief introduction to the genetic measure we use, as well as its advantages and shortcomings. While we only present some main ideas here, Appendix A offers much more detail, and a host of references for the interested reader.

The first point concerns problems linking genetic data to economic behavior. An individual's genome consists of 23 pairs of chromosomes, one from each parent. Each chromosome can be divided into sections that are functionally related, called *genes*. Each gene is comprised of millions of *nucleotide pairs* — these are the "rungs on the ladder" in illustrations of our DNA — and such pairs can take only one of two values.[10] Further, humans only differ from one another in a few million of these pairs (less than 1% of the total). The pairs in which humans may differ are called *single nucleotide polymorphisms*, or SNPs (pronounced "snips").

Once scientists could observe these SNPs (when the human genome was sequenced about 15 years ago) researchers began to link specific SNPs to physical characteristics (e.g., hair color), but also to behavior (e.g., smoking). However, with millions of SNPs, it is not clear how to identify which SNPs are relevant for a particular trait. An initial remedy was to use so-called "candidate genes", identified by theories about biological processes likely to be important for the behavior or outcomes of interest. A multiple-hypothesis testing problem arose, however, given the sheer number of possible candidates, even within a particular gene. This was such a problem that many encouraging results turned out to be false positives (Hewitt, 2012; Benjamin et al., 2012).

These challenges led behavioral geneticists to a new approach, known as genome-wide association studies (or GWAS). In a GWAS, researchers embrace an atheoretical approach and test each SNP individually for a relationship with the outcome of interest. Stringent controls are applied to account for multiple hypothesis testing. Essentially, all SNPs are regressed one by one, along with a set of essential controls. This approach has produced a number of robust, credible results, including the discovery of the most well known genetic variant associated with obesity and several markers associated with smoking (Bierut, 2010; Thorgeirsson et al., 2010). Once a GWAS generates a series of coefficients associated with individual markers, these coefficients can be used to construct genetic indices called *polygenic scores*. These scores are typically linear combinations of dummy variables for individual

[10] Each pair can be an adenine-thymine (AT) pair or a guanine-cytosine (GC) pair. While each rung will be one of these two molecules, the rungs might differ in terms of their relationship to the sides or rails of the ladder. That is, we might have an AT molecule or a TA molecule, where different ends of the rung are connected to different sides of the ladder.

markers. Appendix A provides considerably more detail on how this is done.

Our measure of genetic ability comes directly from a series of landmark GWAS discoveries that have identified some of the first direct associations between specific SNPs and educational attainment (Rietveld et al., 2013; Okbay et al., 2016). After documenting the first GWAS for education (Rietveld et al., 2013), the Social Science and Genetics Consortium recently extended their analysis to perform an educational attainment GWAS with an unprecedented sample size of 293,723 (Okbay et al., 2016). Our genetic measure is the polygenic score developed in this follow-up study, which combines all genotyped SNPs. We refer to this measure as the *EA score*, indicating that "educational attainment" is the trait of interest. In recent work using the HRS, Papageorge and Thom (2016) show that the EA score predicts wages and retirement independently of education. Using a different data set, Belsky et al. (2016) relate an earlier version of the polygenic score we use to a tendency to make financial plans.

We conclude this section by briefly discussing three important caveats and points of clarification. First, it is important to note that the genetic variants used in the construction of this genetic score are not located on sex chromosomes. For this reason, the distribution of these variants should be identical across men and women. Second, we do not claim to estimate *causal effects* of particular genetic variants. Any gene-outcome association that we observe in general reflects a combination of a direct effect and an indirect effect operating through the environments, including those that parents make for their children. Parents with advantageous genetic endowments (which they pass on to their children) are more likely to have the resources or capacity to create better environments. Even so, our measure of an individual's genetic make-up is not *changed* by human capital investments.[11] In contrast, IQ and other cognitive test scores are subject to the critique that they reflect environmental factors, such as earlier human capital investments. For example, Bharadwaj, Løken, and Neilson (2013) find that variation in health care received by newborns has an impact on academic achievement years later.[12] Genetic indices are not subject to this critique because they are fixed at conception.

A final caveat to our use of genetic data is that it may misrepresent ability. Our single measure is not a sufficient statistic for ability, which is surely multi-dimensional. Indeed, a growing literature reflects how there are distinct cognitive abilities (e.g., mathematical ability

[11]However, epigenetic research suggests that environmental factors could work through changes to gene expression, which may be one way that the EA score operates.

[12]Even birth weight, another proxy of innate endowments that has been used in prior literature, is not immune to this critique as it reflects *in utero* investments, e.g., mothers' smoking behavior (Lien and Evans, 2005), exposure to pollutants (Currie, Neidell, and Schmieder, 2009) stress during pregnancy (Camacho, 2008; Currie and Rossin-Slater, 2013) or mothers' own health (Costa, 1998). See also Aizer and Currie (2014) for a recent discussion.

or facility with language), each possessing different associations with economic outcomes (Willis and Rosen, 1979; Heckman, 1995; Cawley et al., 1997). Ability may also encompass not just cognition, but non-cognitive factors as well (Heckman and Rubinstein, 2001).[13] On this point, we are tied to the state of the art in genetics. We do not yet have the tools to credibly determine whether the individual genetic markers that make up the score contribute to distinct abilities.

3 The HRS Sample, the EA Score, and Wealth

In this section, we introduce the data set we use to examine how genetic ability endowments relate to wealth. Section 3.1 provides details on how we construct our sample and provides basic summary statistics. Section 3.2 provides details on our construction of household wealth.

3.1 Sample Construction

The Health and Retirement Study (HRS) is a longitudinal panel study that follows Americans over age 50 and their spouses. Surveys began in 1992 and occur every two years. The HRS collected genetic samples from 15,680 individuals over the course of three waves (2006, 2008, 2010). Although the genetic data for the 2010 wave was publicly released in the spring of 2017, our sample includes only those genotyped in the 2006 and 2008 waves. Individuals in the genotyped sample tend to be born in younger birth cohorts because survival until at least 2006 is required for inclusion. Moreover, women and individuals with more education were more likely to agree to the collection of genetic data.

Our main analysis sample includes all genetically European financial respondents born before 1965 with non-missing genetic, education, and household wealth data.[14] We restrict the sample to European-Americans because the polygenic score we use was discovered in a sample consisting solely of genetic Europeans. We further restrict our sample to include only retired households in years 1996, 1998, and 2002-2010.[15] This restriction aims to balance concerns about measurement error in wealth with concerns about selection biases that arise if

[13] On multidimensionality, Willis and Rosen (1979) emphasize manual skill, which they distinguish from academic skill.

[14] As part of the genetic data release, the HRS also released a file flagging 8,652 individuals as being of European descent based on their genes.

[15] A household is categorized as "retired" 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.

we drop too many observations from our analysis. Further details on wealth data, including measurement problems, are found in the following section.[16]

The resulting analytic sample includes 4,349 financial respondents, with responses supplied for an average of seven waves. Table 1 provides basic descriptives on demographic and educational variables. The mean level of educational attainment is about 13 years, with 21% of the sample obtaining a GED or not graduating from high school and about 21% of the sample earning at least a four year college degree. Roughly 42% of the sample is male. For financial respondents in our analytic sample, Figure 1 plots the sample (kernel-smoothed) density of the EA score variable, the genetic index score we use for our analysis. Values of the score have been demeaned and re-scaled to measure standard deviations relative to the mean. Figure 1 suggests that the distribution of the normalized EA score is approximately normal.

3.2 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 the households' 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, 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.[17]

[16]In a series of robustness checks, discussed in greater detail below, we assess the robustness of our main results to alternative definitions of wealth and to alternative sample construction restrictions. In general, we find that our main results are robust to these alternatives. Results from robustness checks are available in Appendix C.

[17]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

Further, we include the account value of all defined contribution retirement plans.[18] We exclude from our wealth measure values of vehicles and insurance.[19] All monetary values are measured in 2010 dollars.

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. Further details on wealth data, reasons for possible mis-measurement and possible alternative subsamples are found in Appendix B.

Figure 2 shows the unconditional distribution of wealth for observations in our analytic sample. The distribution is right-skewed, which is consistent with a relatively small number of individuals who report very high levels of wealth. Figure 3 shows that the distribution of log wealth is somewhat more normally distributed.[20]

Table 2 shows the 10th, 25th, 50th, 75th, and 90th percentiles of our various wealth measures, as well as the mean. This table contains data on all 15,061 person-year observations with non-missing wealth data. The average age (across the full panel) is 72.9, ranging from 40-101. This age range raises the possibility that our analysis not only captures the relationship between the EA score and wealth accumulation, but also reflects the running down of assets as individuals age post-retirement. However, 75% of the sample is under age 80. The main associations between the EA score and wealth, which we present in next section, are quantitatively similar if we restrict attention to younger subsamples.[21]

The first row of Table 2 shows total wealth winzorized at the 1st and 99th percentiles, including both housing and the present value of all retirement income. The average for our sample is \$567,909. However, the median individual has total wealth of roughly \$304,834, which is substantially lower. Again, this is due to high levels of wealth among individuals in the upper tail; the 10th percentile of wealth is \$31,192, whereas wealth at the 90th percentile is \$1,293,415. The second through fourth rows of Table 2 show wealth excluding the values of

of death in each year conditional on age, cohort and gender of the financial respondent as determined by the Social Security life tables.

[18]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."

[19]Because we focus on retired households, we also exclude *expected* defined benefit and social security income.

[20]Recall from our discussion in Section 2 that the polygenic score does not reflect variants on sex chromosomes, so its distribution is identical in men and women.

[21]Table S2 in Appendix C shows our baseline results for different age restrictions and including working households.

housing, account balances in defined contribution plans, and the present value of retirement income. A few interesting patterns emerge. First, housing makes up a larger portion of total wealth at the lower end of the distribution. For example, at the 10^{th} percentile housing wealth is more than half of total wealth, whereas it accounts for only about one-fourth of total wealth at the 90^{th} percentile. A similar result applies to retirement wealth. In fact, for individuals at the 10^{th} percentile, housing and retirement wealth comprise the entirety of household wealth.

Table 3 shows the median, 75^{th} and 90^{th} percentiles of the individual components of total wealth. At the median, the table confirms that nearly all wealth is in the form of pensions and housing. The 75^{th} percentile includes other sources of wealth, including IRA's, stock holdings, cash, and CDs. At the 90^{th} percentile, wealth is further diversified, including items such as secondary homes and real estate.

4 Genes, Wealth, and Financial Decisions

In this section, we study the relationship between the EA score, wealth, and a host of possible explanatory factors. Results suggest a robust and economically meaningful relationship between household genetic ability and wealth that does not solely operate through higher earnings, inheritances, business ownership, or risk preferences. We demonstrate that the gene-wealth association is, however, substantially mediated by stock market participation, which motivates the analysis in Section 5.

4.1 The EA Score, Household Wealth, and Earnings

Figure 4 presents the main relationship that motivates this paper. The nonparametric, unconditional relationship between the polygenic score of the financial respondent and household wealth, shown by a Lowess plot, is both positive and economically substantial.

In Table 4 we regress wealth on the EA score and various sets of control variables. Unless otherwise indicated, all specifications throughout the paper include wealth winsorized at the 1^{st} and 99^{th} percentiles as well as the following basic controls: the first ten principle components of the genetic data, a full set of birth year dummies, a full set of age dummies, a full set of calendar year dummies, a male dummy, and interactions between the male and age dummies and the male and birth year dummies. As described in Appendix A, controlling for the principal components of the genetic data is a standard practice to account for population stratification and a possible correlation between genetic markers and ethnic ancestry groups (Price et al., 2006; Benjamin et al., 2012). Panel A presents results for the log of wealth, and

Panel B presents results for wealth in levels. The results in Column (1) indicate that a one standard deviation increase in genetic ability is associated with 23.4% higher total wealth (or about $120,453 in levels).[22]

Since the score measures genetic endowments that predict educational attainment, it is natural to examine whether this gradient is primarily driven by education. Column (2) adds controls for the financial respondent's years of schooling and degree, which reduces the coefficient on the polygenic score by more than half; observed educational investments unsurprisingly play a large role in mediating this relationship. In Column (3), the coefficient changes only slightly when controls for parental education are included. This is unsurprising given the strong inter-generational correlation in education. Regardless of education controls, a strong and significant association between wealth and the EA score remains. After controlling for own and parental education, a one-standard-deviation increase in the EA score is associated with a 9.2% increase in wealth at retirement (or about $52,509). We note that while differences in the EA score are associated with large average differences in wealth, the scores explains a small amount of the variance in wealth. This is unsurprising given the high level of dispersion for this outcome. After conditioning on our standard control set (excluding own and parents' education), the incremental R^2 of the EA score is 2.2% Once we control for own and parents' education, it falls to 0.3% For comparison, the EA score predicts 6.1% of the variation in years of schooling in our sample once we condition on our standard control set excluding parents' education.

To better understand the remaining association between wealth and the EA score, we examine a set of "usual suspects" predictors of household wealth. Because the score is directly related to human capital accumulation, an obvious candidate is performance in the labor market. Indeed, Papageorge and Thom (2016) demonstrate that the EA score is associated with higher wages after controlling for education and family background. We also consider measures of inheritance, business ownership, and stock-market participation. Column (1) of Table 5 re-estimates the association between the score and log wealth on the sample of households with non-missing data for each of these additional controls. The coefficient on the EA score is 0.13 for this subsample of households (compared to 0.092 in Table 4). We note that while the sample size is dramatically decreased by these additional restrictions, the coefficient on the EA score remains economically large and highly statistically significant. In Column (2) of Table 5, we include the average of log household income (averaged over all years for which we have non-missing household labor income). Although, as expected, household income predicts higher household wealth, the coefficient on the EA score declines

[22] If we regress average log household wealth on the genetic score along with the principal components discussed in Appendix A, the coefficient on the EA score is 0.253.

modestly, which suggests that household income (near retirement) does not explain much of the gene-wealth gradient. This is not particularly surprising. Papageorge and Thom (2016) find that the EA score predicts differences in labor income only for younger cohorts of the HRS. However, our sample focuses primarily on households in retirement, and thus older cohorts, so we should expect labor income to explain very little of the gene-wealth association for this group. This is confirmed in Appendix C, which shows that the gene-wealth gradient is more meaningfully decreased by labor income once both working (younger) and retired (older) households are included in the sample.

Still, solely controlling for average log household income may not capture important non-linearities in how income relates to the EA score. In a series of robustness checks found in Appendix C, we condition on several different measures of income, including the log of maximum observed household income, quintiles of average log income and quintiles of maximum observed log income. Results remain robust to alternative income measures, though in some cases non-linear income specifications do explain a bit more of the genetic gradient in wealth.

Inter-generational wealth transfers are another possible mechanism linking the EA score with wealth. Individuals receive their genes from their parents, which means high ability individuals with more education will tend to have high ability parents who are more successful, for example, in the labor market. Such parents are also more likely to accumulate wealth to pass on to their children. In Column (3) of Table 5, we add two separate controls for inheritances. First, we add the log of the cumulative value of inheritances received up to and including the current year (plus one). Second, we add a constant binary indicator for whether the individual ever reports receiving inheritances in the HRS data.[23] Adding these inheritance variables reduces the coefficient on the EA score modestly from 0.120 to 0.107.

Entrepreneurship or business ownership has also been linked to systematic differences in wealth (Quadrini, 2000; Erik and Lusardi, 2004). In Column (4) of Table 5, we add an additional control for whether any member of the household has ever reported owning a business. This is the case for approximately 29.1% of individuals in the Table 5 subsample. Business ownership is associated with substantially higher wealth (approx. 22 percent), but does little to moderate the coefficient on the EA score, which declines from 0.107 to 0.099.[24]

Several additional factors not included in Table 5 may be important determinants of the gene-wealth association. One is savings *rates* over the life-cycle. Unfortunately, it is difficult

[23] 43.8% of individuals in this subsample report an inheritance.

[24] One could conduct a more formal mediation analysis (see e.g., MacKinnon (2008) to examine the role of each control in explaining the gene-wealth gradient. However, our aim here is not to make claims about each additional control, but rather to understand the extent to which the gene-wealth gradient is explained by factors that have been suggested in prior literature as important determinants of heterogeneity in wealth.

to estimate savings behavior from the HRS data. Regardless, in Appendix C we use the RAND data based on the Consumption and Activities Mail Survey (CAMS) from the HRS to estimate annual values of consumption. We develop two measures of savings rates, one based on consumption out of total wealth and the other out of total labor income. We find that savings rates are not related to the EA score once we control for wealth. We note, however, that this test is likely under-powered due to noisiness in consumption data and estimates based on households at the end of their working lives (rather than during their prime saving years).[25] This is consistent with findings in Cronqvist and Siegel (2015), who show that there is a genetic basis for savings, but that the genes related to savings are not related to education. We expound on this point further below. Additional factors include retirement age, which can influence social security earnings (Laitner and Silverman, 2012) and has been shown to be associated with the EA score (Papageorge and Thom, 2016), and family composition. In Appendix C, we assess the robustness of results in Table 5 to the inclusion of years since retirement, number of members of the household, and number of children. The results in Table 5 remain qualitatively unchanged when these additional controls are included in the model.

Together, our findings from this section indicate that over half of the genetic gradient in wealth can be explained by education, labor market decisions, and inter-generational wealth transfers. Nevertheless, much remains to be explained. Even after controlling for a host of usual suspects, a one standard deviation increase in the EA score is associated with a 9.9% increase in wealth. The following section investigates the extent to which the gene-wealth association can be explained by financial decisions — in particular, stock market participation.

4.2 Examining the Role of Stock Market Participation

An important component of household wealth accumulation is stock market participation. Both the decision to own stocks and the allocation to stocks conditional on stock ownership greatly impact the returns to household savings (Van Rooij, Lusardi, and Alessie (2011), Favilukis (2013), Poterba (2000)). In Column (5) of Table 5 we add an indicator variable for whether the household has any wealth in stocks in that sample year. Accounting for stock market participation reduces the coefficient on the EA score dramatically, from 0.099 to 0.061. This suggests that portfolio choices and financial decisions in general may represent

[25] One possibility for future research is to follow Dynan, Skinner, and Zeldes (2004) to address noisiness in consumption data by aggregating individuals into groups. Doing so may not help given that we observe consumption when individuals are older, which may be less informative about long-run wealth accumulation.

a critical channel linking genetic ability to household wealth.[26]

In Table 6, we estimate whether the EA score is directly associated with stock market participation. In each specification the dependent variable is a dummy for whether or not the financial respondent's household owns any stocks in that sample year. Column (1) indicates that a one-standard-deviation increase in the EA score is associated with a 3.9 percentage point increase in the probability of stock market participation. Two explanations could rationalize this pattern. First, this could simply reflect the fact that individuals with higher polygenic scores are wealthier, and wealthier people are more likely to invest in risky assets such as stocks (Basak and Cuoco (1998), Vissing-Jørgensen (2002), Alan (2006)). Alternately, this genetic gradient could reflect differences in portfolio choices for a given level of wealth. In Column (2), we add the lag (previous wave) of the log of household wealth as a control variable. Lagged wealth is indeed strongly associated with stock market participation, and its inclusion reduces the coefficient on the EA score to 2.9 percentage points, cutting the association by a little more than one quarter. When the average log household income is included in Column (3), the coefficient is unchanged. The genetic score appears to be associated with stock market participation even after controlling for current wealth and the average of past income.

4.3 Risk Preferences

Given the importance of stock market participation in accounting for the genetic gradient, a natural hypothesis is that the endowments captured by the EA score may operate through risk preferences. To examine this mechanism, we use survey items in the HRS that pose hypothetical questions about a choice between guaranteed total family income or a gamble that might result in a permanent increase or decrease in total family 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: "10 percent, twenty percent, a third, half, seventy-five percent." We create a dummy variable for risk aversion which takes a value of one if an individual always responds with a preference for the job that guarantees current income over the job that might either double income or result in a 10 percent loss.[27] This response indicates the highest degree of

[26]This is consistent with Christelis, Jappelli, and Padula (2010), who find that cognitive abilities are correlated with stock market investments.

[27]One possibility for future research is to follow Kimball, Sahm, and Shapiro (2009), who suggest ways to improve measures of risk aversion in large data sets with noisy measures.

risk aversion permitted with this set of questions, and approximately 32 percent of financial respondents in our basic sample always respond this way.[28]

We explore the relationship between risk aversion, the EA score and wealth in Table 7. In Column (1), the dependent variable is our binary indicator for risk aversion. We find a weak negative association between the EA score and risk aversion — a one-standard-deviation increase in the score is associated with a reduction in the probability of a risk averse response by 1.2 percentage points. However, this association is only marginally significant ($p < 0.10$). In Columns (2)-(3), we revisit our basic specification with the log of total wealth as the dependent variable. Since we only observe the risk aversion measure for a subset of our baseline sample, we first re-estimate our basic specification (Column (3) from Table 4) on the sample with non-missing risk aversion measures. We find a coefficient on the EA score of 0.110. In Column (3), we add our risk aversion dummy. Our measure of risk aversion is informative: risk averse individuals are estimated to have approximately 16 percent less wealth, and this association is significant at the 5% level. However, including this measure of risk aversion has virtually no effect on the coefficient on the EA score, reducing it from 0.110 to 0.108. This suggests that risk preferences, at least as captured by this measure, do not play a major role in explaining the genetic gradient in wealth.

Columns (4)-(5) of Table 7 consider stock market participation. As with total wealth, we first re-estimate our basic specification using the risk aversion subsample. In Column (4) we find that a one-standard-deviation increase in the EA score is associated with a 3.0 percentage point increase in the likelihood of stock ownership. When we add our risk aversion measure in Column (5), the association is unchanged. However, our risk aversion measure is strongly associated with stock ownership; the probability of stock ownership is 6.8 percentage points less likely among risk averse individuals, and this association is highly significant. Taken together, the results in Table 7 indicate a weak negative association between the EA score and risk aversion that explains, at best, only a tiny portion of the relationship between the EA score and wealth.

4.4 Non-Financial Respondent Ability and Household Wealth

Before turning to a more detailed discussion of the EA score and financial decision-making, we briefly assess the robustness of our results if we incorporate the ability of other members of the household. Our analysis until now has only used the ability of the "financial respondent"

[28]One could imagine creating several measures of risk aversion based on this series of questions. For example, one could code individuals as being risk averse based on a different threshold (e.g. taking the guaranteed salary when compared to gamble with a possible loss of one third or more). In results available from the authors, we show that findings in Table 7 are robust to alternate cutoffs.

(FR). Doing so ignores the possibility that household wealth may also be a function of the ability of the financial respondent's spouse, deemed the "non-financial respondent" (NFR).[29]

In Panel A of Table 8, we show that the scores of both the NFR and FR independently predict wealth if we include both in a regression with log wealth as the outcome variable. We restrict the sample to the set of households where both FR and NFR EA scores are available. In Column (1), we regress log wealth (plus one) on the EA score of the FR along with the standard set of controls and obtain a coefficient of 0.097. In Column (2), we include the EA score of the NFR and find that the coefficient on the FR EA score falls modestly to 0.093. We also find that the coefficient on NFR EA score is 0.071; each is statistically significant at the 1% level. In Columns (3) and (4), we repeat the exercise with stock market participation as the outcome variable. If we do not include NFR ability, the coefficient on FR EA score is 0.021. This falls to 0.019 once we control for the NFR EA score. Surprisingly, the coefficient on NFR EA score is larger, estimated at 0.033, and statistically significant at the 1% level.

Together, the results in Panel A of Table 8 provide evidence that the basic gene-wealth associations remain intact if we include the NFR EA score as an additional variable. However, these results also seem to suggest that the FR EA score may not fully capture the ability endowments that are relevant for household wealth outcomes. That is, there may be alternative ways for the ability endowments of each spouse to combine to produce joint household outcomes. The endowments of the FR and the NFR might substitute for one another if an individual's high ability can compensate for the low ability of their spouse. Alternately, spousal abilities might be complementary if high and low ability spouses have to reach compromise positions on financial decisions.

We defer a full analysis of this topic for future work. However, Panel B of Table 8 provides some suggestive evidence that a high ability spouse may compensate for the low ability of the financial respondent. In Column (1), we replicate our baseline wealth regression. In Column (2) we instead measure household ability with the maximum EA score within the household, and the estimated genetic gradient increases by around one-third. In Column (3) we include both the minimum and maximum EA score within the household. Similar results hold in Column (5), where we repeat this exercise for stock market participation.

5 Genes, Financial Literacy, and Expectations

The preceding results suggest that i) there is a substantial relationship between the EA score and household wealth, ii) it is only partially explained by higher income, inheritances, or

[29]Related, spouse risk preferences might be similar (Kimball, Sahm, and Shapiro, 2009), though we have shown that risk preferences do not explain the EA score-wealth gradient.

demographics, and iii) it appears to be mediated by stock market participation, which is a financial choice variable. In this section, we provide further evidence that the polygenic score is associated with many dimensions of financial decision-making. In particular, genetic endowments appear to influence wealth through an ability to process information, which may affect the formation of expectations and the planning horizon for financial decisions. In Section 5.1, we document a relationship between genetic ability and financial literacy. In Section 5.2, we show that individuals with higher values of the EA score report subjective expectations that are closer to objective probabilities, and are less likely to report "extreme" beliefs that treat some outcomes as certainties. In Section 5.3 we show that the financial planning horizon is also associated with the polygenic score, and argue that this relationship is likely due to financial sophistication and ability rather than patience. In Section 5.4, we show that the combination of beliefs and planning horizons reduces the gene-wealth gradient by 25%. In Section 5.5, we provide additional evidence that financial decisions are an important component of the gene-wealth gradient by analyzing those with and without defined benefit pension plans. Finally, in Section 5.6 we explore whether the EA score is related to BMI or smoking, which earlier research has linked to savings behavior (Cronqvist and Siegel, 2015). We show that the EA score likely identifies an alternative mechanism through which genes affect wealth.

5.1 The EA Score and Financial Literacy

A reasonable starting point to evaluate the underlying mechanisms relating genetic ability and wealth is financial literacy (Delavande, Rohwedder, and Willis, 2008). Indeed Lusardi, Michaud, and Mitchell (2017) report over one half of wealth inequality can be attributed to financial knowledge that facilitates access to higher returns. The HRS data contain a questions that directly assess an individual's financial literacy. Unfortunately, these are asked only in a small module in the 2010 wave, which leaves us with fewer than 700 genotyped respondents for these questions. The 2010 module asks three basic financial literacy questions:

- **Compounding Interest:** "First, suppose you had \$100 in a savings account and the interest rate was 2% per year. After 5 years, how much do you think you would have in the account if you left the money to grow — more than \$102, exactly \$102, or less than \$102?"

- **Real Interest Rate:** "Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, would you be able to buy more than today, exactly the same as today, or less than today with the money in this account?"

- **Diversify Stocks:** "Do you think that the following statement is true or false: buying a single company stock usually provides a safer return than a stock mutual fund?"

Columns (1)-(3) of Table 9 present linear probability models explaining whether respondents correctly answered these questions as function of the EA score and our standard set of controls, which includes completed education.[30] The score is positively related to correctly answering the Real Interest Rate and Diversify Stocks questions, but only the coefficient for the Real Interest Rate questions is statistically significant (p-value < 0.10). In Column (4), the dependent variable is an indicator for whether the individual correctly answered all three questions. We find that a one-standard-deviation increase in the EA score is associated with a 3.9 percentage point increase in the probability of correctly answering all questions (p-value <0.10). The financial literacy module also asks a separate question on whether creditors or debtors would be helped by inflation. This question is not asked to the individuals who answered the three questions listed above. Column (5) presents estimates related to a correct answer on this question. The genetic association for this question is statistically significant and economically substantial: a one-standard-deviation increase in the score is associated with an 8 percentage point increase in the probability of a correct answer (p-value < 0.01). Taken together, the results in Table 9 provide evidence that individuals with higher values of the genetic score tend to be more financially literate, after controlling for education.

5.2 The EA Score and Economic Expectations

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. 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). 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 has used HRS data to study the relationship between beliefs and investment behavior (Hudomiet, Kézdi, and Willis, 2011). More closely related to us, Lumsdaine and Potter van Loon (2017) study differences in how individuals report beliefs about stock market returns,

[30] Those responding that they "Don't Know" were coded as not responding correctly.

arguing that their findings reflect heterogeneity in individuals' understanding of the laws of probability.

Here we investigate whether the 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 on a range of events. Individuals are asked to provide a probability on a scale of 0 to 100 for the following three 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?"

The panels of Figure 5 present histograms of the responses, pooling all person-year observations across waves. Across all three questions, we see evidence of heaping at focal probabilities. Specifically, there are pronounced spikes at answers of 0, 50, and 100. It is essential to note that respondents are given specific instructions about the meaning of a response of 0 or 100. That is, they are told to supply these answers if they believe that there is "absolutely no chance" that the event will happen, or if it is "absolutely certain" to happen. All three events can arguably be associated with objective probabilities that should be common knowledge in an economy with fully informed agents. Hudomiet, Kézdi, and Willis (2011) also discuss such "focal point" beliefs, compare them to objective probabilities, and recognize that they correlate with behavior.

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 increased during the year over the period 1992-2015. There is no common definition of an economic depression, but 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.

Table 10 provides estimates of the association between the EA score and individual beliefs about the probabilities of these macroeconomic events. Each panel presents results on a different expectation (Panel A: probability the stock market goes up, Panel B: probability of a depression, Panel C: probability of double digit inflation). Our first measure related to these expectations variables 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 -0.454 suggests that a one-standard-deviation increase in the score is associated with a reduction in the deviation from the objective probability of about one half of a percentage point. Coefficients of -0.346 and -0.614 are estimated for the depression and double-digit inflation questions, respectively.

Of course, the objective probabilities we compute are subject to debate. For robustness, Figure 6 shows the estimated EA score coefficients from Table 10 for values of objective probabilities ranging from 0-100%. Unsurprisingly, there are unrealistic values of objective probabilities that would alter the results in Table 10; however, moderate deviations from our baseline objective probabilities produce economically meaningful and statistically significant results consistent with the results in our baseline specification.

Columns (2)-(4) of Table 10 examine binary outcomes indicating whether respondents answered with specific focal probabilities (0, 50, and 100, respectively). 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, Column (2) of Panel B suggests 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, 6.7 percent of individuals reported a 0% probability for this event.

These results suggest that individuals with lower genetic scores report beliefs that are at odds with objective probabilities and, moreover, tend to heap on "focal" 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.

Table 11 demonstrates the empirical relationship between beliefs, economic behavior, and wealth. In Column (1), we show that individuals who have ever reported a 0% probability of a stock market increase are 21% (percentage points) less wealthy on average. Similar magnitudes are evident for individuals who have ever reported expecting a recession or double-digit inflation with 100% certainty. Individuals who have ever reported a 100% certain belief that stocks will appreciate over the next year are wealthier by 26% on average. This offers preliminary evidence of an important asymmetry in the effect of incorrect beliefs on wealth accumulation. Because stocks historically offer high returns relative to their risk, incorrect but optimistic beliefs are likely to motivate larger stock market investments, which over time are likely to produce faster wealth accumulation. Households that report incorrect but pessimistic beliefs are likely to miss out on these gains. In Column (2) of Table 11 we find the deviations from objective probabilities of macroeconomic events are also negatively correlated with wealth.

For heterogeneity in beliefs about the macroeconomy to generate disparity in wealth, it must be that such beliefs meaningfully inform economic decisions. The most direct mechanism through which beliefs about the stock market would influence wealth accumulation is through stock ownership. Columns (3) and (4) of Table 11 test whether beliefs about the stock market map into actual economic decisions. Column (3) shows that individuals who have ever reported being certain that stock prices will not rise are on average 20 percentage points less likely to participate in the stock market than individuals who have ever reported certainty that prices will increase. Column (4) shows this difference decreases to around 15 percentage points when deviations from object probabilities are included in the regression. This is evidence that household beliefs directly relate to relevant economic choices, and that these choices in turn generate heterogeneity in accumulated wealth.[31]

5.3 The Polygenic Score and Planning Horizon

Another mechanism through which ability may affect wealth is the planning horizon. A well-documented challenge for prudent savings and investment decisions is the complexity associated with inter-temporal 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.

[31] Hudomiet, Kézdi, and Willis (2011) likewise show evidence that focal beliefs predict investment behavior.

Households may be heterogeneous in the costliness of thinking about increasingly distant future periods, and those for whom such considerations are relatively cheap 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?" In Panel A of Table 12, we first construct dummy variables for each household based on the minimum planning horizon reported over the entire sample, and test whether wealth and stock ownership are related to these dummies. Column (1) shows that as the planning horizon increases, so too does wealth. Compared to the baseline of planning for "the next few months", a minimum reported horizon of "the next year" is associated with 37.5% higher wealth. Estimated coefficients increase monotonically with the minimum reported planning horizon, culminating in a coefficient of 1.018 log points for the planning horizon of longer than 10 years. Column (2) shows that stock ownership is also related to the planning horizon, with longer horizons correlating with substantially higher rates of stock market participation.

Columns (3)-(6) in Panel A of Table 12 test whether the EA score predicts planning horizon responses. The dependent variable in Column (3) 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 1.7% increase in the probability of reporting a planning horizon longer than a few months. Columns (4)-(6) repeat this exercise, but with dummies equal to one for increasingly long horizons. The dummy dependent variable in Column (4) is equal to one if the reported horizon is "a few years", in (5) if "5-10 years", and in (6) if "longer than 10 years". In all but Column (6), the coefficient on the EA score is positive and significant at the 5% level. This suggests that the EA score is predictive of longer planning horizons for all but the longest horizon.

A natural question is whether the empirical association between the EA score and the financial planning horizon shown in Table 12 operates through patience. We argue that this is unlikely. First, in a standard dynamic consumption-savings model, small values of the time-preference parameter (β) will make current choices less sensitive to expected future outcomes, but will not remove them from consideration entirely. For patience to affect the planning horizon, low β's would need to be coupled with costs of incorporating each additional time-period into the household's choice problem. But that is precisely the channel implied by heterogeneity in the cost of thinking about distant periods. Further, the regressions in Table 12 demonstrate that even relatively short planning horizon differences, such as a few months versus one year, are predicted by the EA score. Even with costly information, for patience to explain planning horizon differences on the order of less than one year would require β values to be dramatically smaller than the smallest estimates in the existing literature.

Gabaix and Laibson (2017) provide a theoretical foundation for our interpretation. They demonstrate that infinitely patient, bayesian households that generate noisy, unbiased signals about future events will behave *as if they are impatient*. A consequence of their model is that households that generate more precise signals will appear to behave as if they are more patient than others, even though all households are equally (infinitely) patient.

Regardless, data from HRS modules on time preference allow us to directly test the association between the financial planning horizon and patience. In 2014, the HRS asked 599 respondents a series of questions of the form "Would you rather receive 100 Dollars today or X Dollars in 12 months?", where the amount received in 12 months was varied. These questions allow us to estimate an annual discount factor, $\widehat{\beta}$, for each person. Unfortunately, we only have 763 person-year observations for 208 financial respondents with non-missing discount factors and genetic data. This small sample size leaves us severely under-powered to test whether elicited time preferences mediate the relationship between the EA score and wealth.[32] However, we can examine whether there is a relationship between $\widehat{\beta}$ and the planning horizon that is sufficiently large to rationalize the gradient we observe. Panel B of Table 12 presents the average value of $\widehat{\beta}$ for individuals indicating each category of the planning horizon in a given year.[33] There is a monotonic increase in the average elicited $\widehat{\beta}$ as one moves to higher planning horizon categories. However, these average differences are modest compared to the average wealth differences by planning horizon found in Panel A. For example, individuals in the lowest horizon category ("the next few months") and the highest horizon category ("longer than 10 years") exhibit average discount factors that differ by 0.098, which is approximately one half of the standard deviation of $\widehat{\beta}$ in our sample (0.18). By contrast, the average differences in household wealth between these two groups exceeds 100 log points. This suggests that the financial planning horizon variable must be capturing much more than just patience.

[32] In a cross sectional regression of the discount factor on the EA score with standard controls for this group, we find no association between $\widehat{\beta}$ and the EA score.

[33] Note that the discount factor is elicited only in one year, so this is a time-invariant characteristic. The financial planning horizon question is asked repeatedly, so the means in Panel B of Table 12 average over multiple person-year observations, with a respondent potentially contributing more than one person-year observation.

5.4 Wealth, Beliefs, Planning, and Financial Decisions

The results in Tables 10 - 12 suggest that the relationship between the EA score and wealth may partially operate through beliefs and financial decisions; the EA score is related to both beliefs and the planning horizon, and both are strongly related to wealth. In Table 13, we include these variables in a regression of wealth on the EA score to test whether they mediate any of the gene-wealth gradient.

Column (1) of Table 13 reports results from our baseline regression of wealth on the EA score for the sample of households with non-missing expectations and financial planning horizons. The coefficient on the EA score in this specification is 0.090. In Column (2), we include the full set of belief variables, including dummies for whether a 0% or 100% probability was ever given for any of the three macroeconomic events, as well as the maximum of the deviation from the objectively correct probabilities. Including this set of belief variables reduces the coefficient on the EA score to 0.087 (a 3.3% reduction). While this is a modest change, it is somewhat expected. Households are likely to consider a wide range of economically relevant probabilities when making decisions, of which we only observe three. Beliefs about future health, the housing market, retirement, the political climate, and many other relevant factors combine to influence economic choices. Column (3) includes the financial planning horizon dummies; here we see a much larger moderation of the coefficient on the EA score, shrinking from 0.90 to 0.74, an 18% decrease. Finally, in Column (4) we include both expectations and planning horizon controls. In total, these variables reduce the coefficient on the EA score by a full 20%.

Table 13 provides evidence that macroeconomic expectations and the planning horizon are important components of the relationship between the polygenic score and wealth. While economic beliefs and the planning horizon cannot explain the entire gene-wealth gradient, they moderate a significant portion of it. This is particularly notable given the likelihood of noise and measurement error inherent in reported expectations. If the complexity associated with economic decisions heightens the disparity in wealth between low- and high-ability individuals, this suggests that more paternalistic policies that reduce the burden of financial decisions may disproportionately benefit those at the low-end of the wealth distribution.

5.5 Defined Benefit Pensions and Limited Autonomy

A consequence of the apparent relationship between genetic ability, financial literacy, beliefs, and financial decisions is that individuals with low EA scores may benefit from outsourcing certain economic choices. Saving and investment decisions are two immediate examples. Defined benefit pensions, which are offered through 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.

One primary concern with this approach is that pension participation is not randomly assigned. As a first step, we regress an indicator for defined benefit pension participation on the EA score.[34] Column (1) of Table 14 shows that after including our standard set of controls, there is no economically meaningful 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 appear to be uncorrelated with genetic ability after controlling for education.

Columns (3)-(5) in Table 14 investigate whether participation in a defined benefit plan mitigates the role of ability in wealth accumulation. Column (3) shows that participation in a defined benefit plan is associated with a 46 percent increase in wealth. In Column (4), we also include an interaction between the EA score and the pension-participation dummy. 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 0.046, compared to 0.135 for households that do not participate in a defined benefit plan. Said differently, the EA score is nearly three times as important 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 ability to make wise financial choices.

In Column (5) of Table 14, we directly test whether defined benefit pensions reduce the gene-wealth gradient by protecting individuals from financial mistakes or incorrect beliefs. We include (maximum) deviations from objective beliefs about the stock market, the likelihood of a depression, and the probability of double digit inflation (Column (1) from Table 10), and interact these with the defined benefit pension dummy. We continue to find significant negative relationships between each of these deviation variables and household wealth. However, we also find significant positive interactions between the defined benefit indicator and each of these deviations. This suggests that the consequences of inaccurate

[34] 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.

beliefs may be less pronounced for people who are faced with fewer investment decisions. When these interactions are included, the interaction between the EA score and the defined pension dummy is reduced in magnitude from -0.089 to -0.068 and becomes significant only at the 10% level. Columns (4) and (5) offer more evidence that the genetic endowments we study operate at least in part through expectations, and that disparities arising from these endowments can be mitigated by policies that require fewer household financial decisions.

5.6 Alternate Mechanisms

Thus far, our results suggest that financial sophistication and information processing, working through expectations and the planning horizon, are likely mechanisms linking genetic endowments for education with wealth accumulation. However, it is plausible that the EA score also measures genetic factors that operate through other channels. In particular, Cronqvist and Siegel (2015) provide evidence that the genetic endowments that drive savings and wealth may work through time preference and self-control. Using twin study methods, they demonstrate a genetic correlation between savings, obesity, and smoking. Given the role of time preference and self-control in governing health behaviors such as food intake or cigarette consumption, Cronqvist and Siegel (2015) suggest that these mechanisms are likely to also play an important role in the genetic basis for wealth. This raises the possibility that the EA score also captures genes related to self-control and time preference, and that these traits provide a common genetic basis for education, smoking, BMI, and wealth. Alternately, the genes summarized in the EA score may capture additional, distinct behavioral channels that drive wealth.

To assess these possibilities, we utilize additional polygenic scores that have been developed for BMI and smoking. These scores are constructed using the same methods used to develop the EA score from Okbay et al. (2016). For obesity we use a polygenic score developed to predict BMI based on the estimates of Locke et al. (2015), and for smoking, we use a score developed to predict the number of cigarettes smoked per day (CPD) at peak consumption, based on the estimates of Thorgeirsson et al. (2010). All scores have been standardized to have a mean of zero and a standard deviation of one.

To begin, Panel A of Table 15 presents the simple correlations between the polygenic scores for education, BMI, and cigarettes per day. We find negative correlations between the EA score and the other two polygenic scores. However, these correlations are relatively modest (-0.18 for BMI and -0.10 for cigarettes). In Column (1) of Panel B, we add the BMI and smoking scores to our baseline specification on the log of total wealth (Column (3) of Table 4). The polygenic scores for BMI and CPD are both negatively correlated with wealth and are statistically significant at the 1% and 5% levels, respectively, consistent with the results from Cronqvist and Siegel (2015). A one-standard-deviation increase in the score for BMI is associated with approximately 5.7 percent lower wealth. This association is 4.9 percent for the CPD score. These results provide an important cross-validation of results in Cronqvist and Siegel (2015), which were generated using twin studies.

Column (1) of Panel B also shows that the inclusion of the BMI and CPD scores has little effect on the EA score coefficient, which is still economically large and statistically significant (0.080 compared to 0.092 for the baseline). It is noteworthy that all three scores independently predict wealth. This could arise either because all three scores measure the same latent genetic endowments with error, or because they indeed reflect distinct genetic factors. To explore this further, we examine whether these other polygenic scores also predict extreme expectations. Columns (2)-(4) in Table 15 re-estimate our specifications on deviations from objective beliefs about the stock market, the likelihood of a depression, and the probability of double digit inflation (Column (1) from Table 10). While we continue to find a negative association between the EA score and deviations from objective beliefs, we find no statistically significant relationships between the BMI and CPD scores and these deviations.[35] This suggests that genes related to education, smoking, and obesity all appear to predict wealth, but through different mechanisms.

The results presented here have several implications for heterogeneity in the wealth accumulation process. First, while twins studies have established the importance of genes for wealth, there appear to be multiple distinct genetic mechanisms. One source of genetic heterogeneity may work through time preference and self control, which affect savings along with health behaviors. We also find evidence for a separate source of heterogeneity — linked to human capital accumulation — which may work through information processing and expectations formation.[36] Because time preference and other savings-based mechanisms cannot explain persistent differences in *returns* to wealth, evidence for a genetic mechanism related to information and decision-making offers a possible biological micro-foundation for the kind

[35] In separate analyses available upon request, we replicate every regression in Table 10, adding in all three polygenic scores. We continue to find statistically significant, negative associations between the EA score and the likelihood that an individual provides an extreme probability in either direction for all three expectation outcomes. For the BMI and CPD scores, we find only marginally significant ($p < 0.10$) associations for two out of twelve associations, but otherwise find no statistically significant relationships between the scores and extreme beliefs. We do, however find that the BMI and CPD scores appear to be negatively associated with the probability of providing a subjective probability of exactly 0.50 for the stock market question (significant at the 0.05 and 0.10 levels, respectively). However, we note that we do not find the same pattern for the depression or inflation questions. We never find a statistically significant relationship between the EA score and providing a subjective belief of 0.50 for any question.

[36] These results are also consistent with our findings that consumption-wealth and income-wealth ratios do not appear to be related to the EA score once we control for wealth. Those results are available in Appendix C.

of heterogeneity described by Benhabib, Bisin, and Zhu (2011). Moreover, because this mechanism affects decision-making and not preferences, this raises the possibility that policies targeting information or assistance in financial choices could impact wealth inequality due to genetic variation.

5.7 Childhood SES and Macroeconomic Expectations

The results of the preceding sections provide evidence that the genetic endowments measured by the EA score operate through channels related to financial decision-making, probabilistic thinking, and expectations formation. Furthermore, we show that policies that reduce the burden of complex financial choices (e.g. promoting defined benefit pensions) may mitigate the consequences of poor financial decision-making.

An alternative policy response would focus on improving the quality of financial decision-making and expectations, thus moderating the link between the EA score and these channels. Household socioeconomic status (SES) during childhood might affect the relationship between genetic endowments and financial skills (Kuhnen and Miu (2017), Das and Kuhnen (2017)). Individuals with disadvantageous ability endowments, but who are born into high-SES environments, may have access to resources and investments that would improve their ability to form expectations or to process information.

We test whether high childhood SES mitigates the likelihood that individuals report incorrect beliefs. We consider four retrospective childhood SES measures: whether or not the individual grew up in poverty; average income of father's occupation; whether the family ever moved or asked for help due to financial difficulties; and whether the individual's father was ever unemployed for long periods of time. Previous work by Papageorge and Thom (2016) suggests that these four SES measures moderate the relationship between the EA score and educational attainment. In each panel of Table 16, our dependent variable is the absolute value of the deviation of an individuals' subjective probability from the objective probability of a macroeconomic event. Each column measures SES using a different binary indicator. Each estimate replicates the specification from Column (1) of Table 10, regressing the deviation on our standard controls, but also adding an SES measure and an interaction between SES and the EA score. Despite a few significant coefficients, we find no consistent evidence that childhood SES is associated with the accuracy of adult beliefs, or moderates the relationship between the EA score and beliefs.

These results suggest that parental resources may not effectively address differences in ability endowments that are associated with difficulties thinking probabilistically. Of course, much more research is needed to assess whether this early evidence survives more rigorous analysis. Still, our results provide support for policies, such as public pension schemes, that may mitigate inequality due to poor financial decision-making.

6 Conclusion

This paper shows that the same genetic endowments that predict educational attainment and earnings are also associated with higher wealth. This could arise purely from an association between ability and earnings, as high earnings will mechanically generate high wealth. We show that controlling for education and earnings does indeed attenuate the genetic gradient in wealth, but only accounts for roughly one half of the association. Stock market participation accounts for one third of the remaining gradient in wealth, which suggests financial decision-making as another mechanism linking labor market ability and wealth. We show that those with a higher polygenic score perform better on standard financial literacy questions, and are less likely to report extreme beliefs about the economy, including the likelihood of stock market appreciation or a severe recession.

We also show evidence that childhood SES does not appear to modify the relationship between the polygenic score and beliefs. This is troubling as it suggests that reallocating resources for educational investments is not an easy solution for difficulties in financial decision-making. On the other hand, we show that the genetic gradient in wealth is weaker among individuals who have less autonomy in their financial decisions due to participation in traditional pension plans, while participation in pensions is not itself predicted by the polygenic score. Our findings suggest that policies that reduce autonomy in financial decision-making, such as public pension schemes, might play an important role in reducing wealth inequality. This is particularly important given our findings that the same ability endowments that predict low earnings also predict disadvantageous financial decision-making, which could further exacerbate wealth inequality among the elderly.

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7 Tables and Figures

Table 1: Summary Statistics

Variable	Mean	Std. Dev.	N
Male	0.42	0.49	4349
Birth Year:			
< 1930	0.33	0.47	4349
1930-1934	0.19	0.4	4349
1935-1939	0.21	0.41	4349
1940-1944	0.15	0.35	4349
1945-1949	0.07	0.25	4349
1950-1954	0.05	0.21	4349
Education (Years)	12.87	2.57	4349
Highest Degree:			
None	0.16	0.37	4345
GED	0.05	0.21	4345
High School	0.54	0.5	4345
College (2 year)	0.04	0.21	4345
College (4 year)	0.12	0.33	4345
Masters	0.07	0.25	4345
Advanced	0.02	0.14	4345
Yrs. of ed: Father	9.74	3.6	3118
Yrs. of ed: Mother	10.24	3.1	3251

Notes: Summary statistics for our main cross-sectional sample of financial respondents.

Table 2: Wealth Distribution

	p10	p25	p50	p75	p90	Mean	St Dev
Wealth (Winz)	31,192	112,539	304,834	668,583	1,293,415	567,909	856,701
Wealth (No Housing)	13,853	49,749	168,341	457,852	975,624	440,273	1,393,031
Wealth (No Ret. Wealth)	1,154	65,000	221,734	546,905	1,119,484	493,999	1,088,254
Wealth (No H or R)	0	5,408	83,285	325,526	807,975	329,394	955,615

Notes: Wealth mean and distribution (10th, 25th, 50th, 75th and 90th percentiles) for total wealth, non-housing wealth, non-retirement wealth and wealth that includes neither retirement wealth nor housing. These statistics are calculated for the full sample of 15,061 household-year observations with non-missing wealth data.

Table 3: Components of Wealth

	(1) **p50**	(2) **p75**	(3) **p90**	(4) **Mean**	(5) **Med Share**	(6) **Mean Share**
Ret Plans (Employer)	0	0	0	21,683	0.00	0.01
Ret Inc (PV)	39,170	97,070	207,812	84,835	0.16	0.32
Real Estate	0	0	53,511	45,417	0.00	0.03
Business	0	0	0	35,484	0.00	0.02
IRAs	0	54,690	202,557	72,091	0.00	0.09
Stocks	0	29,204	216,325	91,031	0.00	0.08
Cash Equiv	8,102	30,000	80,804	33,137	0.03	0.09
CDs	0	5,408	60,000	23,188	0.00	0.04
Bonds	0	0	0	14,861	0.00	0.01
Other Assets	0	0	16,000	14,489	0.00	0.02
Other Debts	0	0	4,848	2,538	0.00	0.07
Trusts	0	0	0	2,234	0.00	0.00
Home Value	115,435	205,509	354,475	162,631	0.31	0.50
Mortgage	0	0	55,000	15,580	0.00	0.15
Home Loan	0	0	0	2,287	0.00	0.01
Second Home	0	0	25,000	21,860	0.00	0.03
Second Morgt.	0	0	0	1,288	0.00	0.01

Notes: Summary statistics of different sources of wealth (mean and distribution, including the 50th, 75th and 90th percentiles). Columns 5 and 6 are median and mean share, respectively, of each component in total wealth. 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.

Table 4: The Polygenic Score and Wealth

Panel A: log Wealth			
	(1)	(2)	(3)
EA Score	0.234***	0.097***	0.092***
	(0.023)	(0.022)	(0.022)
Resp Education	No	Yes	Yes
Parental Education	No	No	Yes
Obs.	14,766	14,766	14,766
R^2	0.158	0.266	0.270

Panel B: Wealth (level)			
	(1)	(2)	(3)
EA Score	120,453***	55,830***	52,509***
	(13,256)	(12,568)	(12,623)
Resp Education	No	Yes	Yes
Parental Education	No	No	Yes
Obs.	15,061	15,061	15,061
R^2	0.093	0.178	0.181

Notes: Significance stars ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. All regressions include the following *standard set of controls*: first ten principal components of the genetic data, a full set of birth year dummies, age dummies, calendar year dummies, a male dummy, interactions between the birth year and male dummies, interactions between the age and male dummies, a dummy variable for individuals in 2002 with dormant retirement accounts, and an interaction between the EA score and the indicator for dormant accounts. Column (2) adds controls for the financial respondent's own education: years of education, and a full set of dummies for degrees. Column (3) adds controls for parental education: years of education for the respondent's father and mother, respectively, along with dummy variables indicating missing values for either. Standard errors are clustered at the household level. We use data on all household-year observations where each member of the household is either not working for pay or is retired.

Table 5: Total Wealth, Income Flows, and Financial Decisions

Dep. Var: log Wealth	(1)	(2)	(3)	(4)	(5)
EA Score	0.129***	0.120***	0.107***	0.099***	0.061**
	(0.029)	(0.027)	(0.027)	(0.027)	(0.024)
Avg log HH Inc		0.398***	0.384***	0.388***	0.310***
		(0.037)	(0.037)	(0.037)	(0.031)
log Sum Inher.			0.023***	0.022***	0.014*
			(0.008)	(0.008)	(0.007)
Ever Rec Inher.			0.151	0.153	0.119
			(0.095)	(0.095)	(0.081)
Ever Own Bus.				0.221***	0.202***
				(0.054)	(0.048)
Owns Stocks					1.043***
					(0.043)
Obs.	7,151	7,151	7,151	7,151	7,151
R^2	0.287	0.340	0.355	0.359	0.457

Notes: Significance stars ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. The dependent variable in all specifications is the log of total wealth, as used in Table 4. All regressions include the standard set of controls outlined in the Notes to Table 4, as well as controls for the respondent's education (years of schooling and a fully set of degree dummies), and controls for mother's and father's education. Standard errors are clustered at the household level. To allow for comparability of coefficients across specifications, we restrict the sample in all specifications to households with non-missing observations on average household income, inheritances, business ownership, and stock ownership. We use data on all household-year observations where each member of the household is either not working for pay or is retired.

Table 6: Polygenic Score and Stock Ownership

Dep. Var: Owns Stocks	(1)	(2)	(3)
EA Score	0.039***	0.029***	0.029***
	(0.009)	(0.010)	(0.010)
Lag of log Wealth		0.152***	0.149***
		(0.008)	(0.009)
Avg log HH Inc			0.017
			(0.010)
Obs.	8,035	5,047	5,047
R^2	0.213	0.366	0.366

Notes: Significance stars ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. The dependent variable in all specifications is a dummy variable indicating whether the household owns any stocks or stock mutual funds. All regressions include the standard set of controls outlined in the Notes to 4, as well as controls for the respondent's education (years of schooling and a full set of degree dummies), and controls for mother's and father's education. Standard errors are clustered at the household level. We use data on all household-year observations where each member of the household is either not working for pay or is retired. For Columns (2)-(3), we further restrict the sample to households where each member is either not working for pay or is retired in the previous period.

Table 7: Risk Aversion, Wealth, and Stock Ownership

	(1)	(2)	(3)	(4)	(5)
Dep Var:	**Risk Averse**	**log Wealth**	**log Wealth**	**Owns Stocks**	**Owns Stocks**
EA Score	-0.012*	0.110***	0.108***	0.030***	0.030***
	(0.006)	(0.031)	(0.031)	(0.010)	(0.010)
Risk Averse			-0.158**		-0.068***
			(0.064)		(0.020)
Obs.	5,346	6,752	6,752	7,139	7,139
R^2	0.104	0.278	0.280	0.215	0.219

Notes: Significance stars ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. The dependent variable in Column (1) is a binary measure for risk aversion described in Section 4.3. The dependent variable in Column (2)-(3) is the log of total household wealth. The dependent variable in Columns (4)-(5) is a binary for any stock ownership. Since the risk aversion measure is time-invariant (whether an individual ever reported the most risk averse response), we only use one observation per individual and include a slightly different control set that includes the genetic principal components, birth year dummies, a male dummy, interactions between birth year dummies and the male dummy, and the own and parental education controls. All other regressions include the standard set of controls outlined in the Notes to Table 4, as well as controls for own and parental education. Standard errors are clustered at the household level. Note as well that the sample for Column (1) includes all individuals with non-missing risk aversion data, regardless of whether they are a financial respondent.

Table 8: Non-Financial Respondent Score and Household Wealth

Panel A: Spouse's Score

	(1)	(2)	(3)	(4)
Dep Var:	**log Wealth**	**log Wealth**	**Owns Stocks**	**Owns Stocks**
EA Score	0.097***	0.093***	0.021*	0.019*
	(0.027)	(0.027)	(0.011)	(0.011)
EA Spouse		0.071***		0.033***
		(0.025)		(0.011)
Obs.	5,202	5,202	5,189	5,189
R^2	0.324	0.328	0.228	0.232

Panel B: Max Score

	(1)	(2)	(3)	(4)	(5)	(6)
Dep Var:	**log Wealth**	**log Wealth**	**log Wealth**	**Owns Stocks**	**Owns Stocks**	**Owns Stocks**
EA Score	0.097***			0.021*		
	(0.027)			(0.011)		
Min EA Score			0.063*			0.024
			(0.037)			(0.016)
Max EA Score		0.131***	0.099***		0.041***	0.029*
		(0.031)	(0.035)		(0.014)	(0.016)
Obs.	5,202	5,202	5,202	5,189	5,189	5,189
R^2	0.324	0.326	0.328	0.228	0.231	0.231

Notes: Significance stars ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. The dependent variable in all specifications is the log of total household wealth. All other regressions include the standard set of controls outlined in the Notes to Table 4, as well as controls for own and parental education. Standard errors are clustered at the household level. The samples for Columns (1) and (3) of Panel A have been restricted to observations of financial respondents with non-missing values for the spousal EA score.

Table 9: EA Score and Financial Literacy

Dep Var:	(1) **Compound Interest**	(2) **Real Interest**	(3) **Diversify**	(4) **All Correct (1)-(3)**	(5) **Inflation and Lending**
EA Score	-0.001	0.030*	0.027	0.039*	0.080***
	(0.018)	(0.016)	(0.021)	(0.021)	(0.020)
Obs.	670	671	671	667	676
R^2	0.246	0.202	0.243	0.295	0.272

Notes: Significance stars ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. The dependent variables in Columns (1)-(3) are dummy variables indicating correct responses for the three questions that were included together in a financial literacy module in the 2010 wave of the HRS. The dependent variable in Column (4) aggregates these items by constructing a binary indicator for whether the individual got all three questions correct. The dependent variable in Column (5) indicates a correct response to a separate module question (with different respondents) on inflation and lending (see text for details). All regressions include the standard set of controls outlined in the Notes to Table 4 (except for the dormant pension controls), as well as controls for own and parental education. Standard errors are clustered at the household level.

Table 10: EA Score and Beliefs

	(1) **Dev. from Objective**	(2) **0% Prob**	(3) **50% Prob**	(4) **100% Prob**
Panel A: Market Up				
EA Score	-0.454***	-0.004***	-0.001	-0.003**
	(0.141)	(0.001)	(0.003)	(0.001)
Obs.	39,743	39,743	39,743	39,743
R^2	0.071	0.031	0.012	0.022
Panel B: U.S. Depression				
EA Score	-0.346***	-0.005***	-0.002	-0.004**
	(0.125)	(0.002)	(0.003)	(0.002)
Obs.	33,048	33,048	33,048	33,048
R^2	0.065	0.031	0.022	0.045
Panel C: Double Digit Inf				
EA Score	-0.614***	-0.007***	0.000	-0.007***
	(0.184)	(0.002)	(0.004)	(0.002)
Obs.	19,551	19,551	19,551	19,551
R^2	0.050	0.027	0.023	0.040

Notes: Significance stars ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. All regressions include the standard set of controls outlined in the Notes to Table 4 (excluding the dormant pension controls), as well as controls for own and parental education. The samples for all regressions in this table include person-year observations on all respondents (not just financial respondents with non-missing wealth data). Standard errors are clustered at the household level.

Table 11: Beliefs and Household Wealth

	(1) **log Wealth**	(2) **log Wealth**	(3) **Owns Stocks**	(4) **Owns Stocks**
Ever Pr Mrkt Up 0%	-0.205***	-0.109*	-0.098***	-0.055***
	(0.054)	(0.063)	(0.017)	(0.021)
Ever Pr Mrkt Up 100%	0.261***	0.261***	0.101***	0.099***
	(0.063)	(0.063)	(0.021)	(0.021)
Ever Pr Rec 0%	-0.013	0.019	-0.023	-0.016
	(0.055)	(0.056)	(0.018)	(0.018)
Ever Pr Rec 100%	-0.264***	-0.017	-0.061***	0.000
	(0.059)	(0.079)	(0.018)	(0.025)
Ever DD Inf 0%	-0.103	-0.108	-0.003	-0.003
	(0.067)	(0.066)	(0.021)	(0.021)
Ever DD Inf 100%	-0.212***	-0.153	-0.087***	-0.063**
	(0.069)	(0.093)	(0.020)	(0.029)
Max Dev Mrkt. Up		-0.003**		-0.002***
		(0.001)		(0.000)
Max Dev Rec.		-0.008***		-0.002***
		(0.002)		(0.001)
Max Dev DD Inf		-0.001		-0.000
		(0.002)		(0.001)
Obs.	13,655	13,655	14,093	14,093
R^2	0.278	0.283	0.201	0.206

Notes: Significance stars ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. All regressions include the standard set of controls outlined in the Notes to Table 4 (excluding the dormant pension controls), as well as controls for own and parental education. Standard errors are clustered at the household level.

Table 12: Financial Planning Horizons and Discount Factors

Panel A: The Planning Horizon, Wealth, and the EA score

	(1) **log Wealth**	(2) **Owns Stocks**	(3) **Planning Horiz. ≥ 1 Year**	(4) **Planning Horiz. ≥ Few Yrs**	(5) **Planning Horiz. ≥ 5-10 Yrs**	(6) **Planning Horiz. > 10 Yrs**
Plan. Horizon:						
Next Year	0.375***	0.095***				
	(0.054)	(0.017)				
Next Few Yrs	0.633***	0.155***				
	(0.049)	(0.016)				
Next 5-10 Yrs	0.821***	0.230***				
	(0.069)	(0.024)				
> 10 Yrs	1.018***	0.179***				
	(0.153)	(0.052)				
EA Score	0.078***	0.024***	0.017***	0.017***	0.010**	-0.000
	(0.021)	(0.007)	(0.005)	(0.006)	(0.004)	(0.001)
Obs.	14,702	15,341	8,526	8,526	8,526	8,526
R^2	0.306	0.216	0.050	0.049	0.042	0.030

Panel B: The Planning Horizon and Discount Factors

Plan. Horizon:	Avg. Discount Factor	Obs.
Next Few Months	0.601	261
Next Year	0.645	240
Next Few Yrs	0.668	534
Next 5-10 Yrs	0.679	550
> 10 Yrs	0.699	190

Notes: Significance stars ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. All regressions include the standard set of controls outlined in the Notes to Table 4 (excluding the dormant pension controls), as well as controls for own and parental education. The samples for all regressions in this table include person-year observations on all respondents (not just financial respondents with non-missing wealth data). Standard errors are clustered at the household level.

Table 13: Moderating the Relationship Between the EA Score and Wealth

	(1) **log Wealth**	(2) **log Wealth**	(3) **log Wealth**	(4) **log Wealth**
EA Score	0.090***	0.087***	0.074***	0.072***
	(0.027)	(0.026)	(0.026)	(0.025)
Standard Controls	Yes	Yes	Yes	Yes
Belief Controls	No	Yes	No	Yes
Planning Horizon Controls	No	No	Yes	Yes
Obs.	7599	7599	7599	7599
R^2	0.351	0.364	0.383	0.393

Notes: Significance stars ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. All regressions include the standard set of controls outlined in the Notes to Table 4 (excluding the dormant pension controls), as well as controls for own and parental education. The samples for all regressions in this table include person-year observations on all respondents (not just financial respondents with non-missing wealth data). Standard errors are clustered at the household level.

Table 14: Pensions and Household Wealth

	(1) **Has Pension**	(2) **log Pension Wealth**	(3) **log Wealth**	(4) **log Wealth**	(5) **log Wealth**
EA Score	-0.004	0.021	0.088***	0.135***	0.115***
	(0.008)	(0.022)	(0.022)	(0.035)	(0.035)
DB Pension			0.459***	2.376**	1.644
			(0.039)	(1.129)	(1.109)
EA Score x DB				-0.089**	-0.068*
				(0.038)	(0.038)
Max Dev Mrkt. Up					-0.007***
					(0.002)
Max Dev Rec.					-0.011***
					(0.002)
Max Dev DD Inf					-0.005**
					(0.002)
(Max Dev Mrkt. Up) x DB					0.004**
					(0.002)
(Max Dev Rec.) x DB					0.006**
					(0.003)
(Max Dev DD Inf) x DB					0.005**
					(0.002)
Obs.	13,655	7,727	13,655	13,655	13,655
R^2	0.083	0.643	0.287	0.292	0.310

Notes: Significance stars ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. All specifications start with the basic specification for log wealth in Column (3) of Table 4. Standard errors are clustered at the household level. Columns (3)-(5) also include a full set of interactions between the principal components of the genetic data and the defined benefit pension dummy. This explains the large coefficient on DB Pension in those specifications.

Table 15: Household Wealth, Expectations, and Other Scores

Panel A: Correlations between Polygenic Scores:

	EA Score	BMI Score	CPD Score
EA Score	1.00		
BMI Score	-0.18	1.00	
CPD Score	-0.10	0.03	1.00

Panel B: Other Scores, Wealth, and Expectations:

	(1) **log Wealth**	(2) **Dev. from Objective: Market Up**	(3) **Dev. from Objective: Depression**	(4) **Dev. from Objective: Double Digit Inf.**
EA Score	0.080***	-0.452***	-0.314**	-0.582***
	(0.022)	(0.144)	(0.128)	(0.187)
BMI Score	-0.057***	0.074	0.142	0.017
	(0.021)	(0.140)	(0.120)	(0.183)
CPD Score	-0.049**	0.077	0.138	0.048
	(0.021)	(0.138)	(0.120)	(0.177)
Obs.	14,575	39,288	32,686	19,335
R^2	0.271	0.071	0.066	0.050

Notes: Significance stars ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. Panel A shows the cross-sectional correlations for the 4,296 financial respondents from our baseline sample with non-missing values of all polygenic scores. Column (1) in panel B replicates the basic log wealth regression from Table 4 but now includes all three polygenic scores. Columns (2)-(4) in panel B replicate the specifications from Column (1) of Table 10, including all three polygenic scores.

Table 16: Beliefs and Childhood SES

	(1)	(2)	(3)	(4)
	Not Poverty	**Income**	**Move or Help**	**Father Unemployed**
Panel A: Stock Market Up				
High SES	-14.068*	9.956	16.103**	4.535
	(7.614)	(7.949)	(8.054)	(7.759)
EA Score	-0.792***	-0.754***	-0.808***	-0.712**
	(0.281)	(0.241)	(0.283)	(0.279)
EA × High SES	-0.299	-0.325	-0.328	-0.406
	(0.322)	(0.320)	(0.323)	(0.319)
Obs.	39,209	30,590	39,161	39,324
R^2	0.059	0.058	0.059	0.058
Panel B: Recession				
High SES	-4.378	2.705	8.368	-0.519
	(6.588)	(6.683)	(7.132)	(6.846)
EA Score	-0.767***	-0.448**	-0.745***	-0.595**
	(0.237)	(0.210)	(0.244)	(0.243)
EA × High SES	0.166	-0.290	0.153	-0.055
	(0.277)	(0.275)	(0.282)	(0.281)
Obs.	32,624	26,203	32,534	32,687
R^2	0.061	0.061	0.062	0.060
Panel C: Double Digit Inflation				
High SES	-12.480	10.337	-4.046	-1.266
	(9.970)	(9.519)	(11.292)	(10.119)
EA Score	-0.643*	-0.299	-0.943**	-0.766**
	(0.361)	(0.285)	(0.382)	(0.357)
EA × High SES	-0.502	-1.374***	-0.129	-0.385
	(0.416)	(0.376)	(0.431)	(0.413)
Obs.	19,300	17,464	19,264	19,322
R^2	0.043	0.045	0.043	0.042

Notes: Significance stars ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. All specifications start with the basic specification for deviations from objective beliefs found in Column (1) of Table 10. Standard errors are clustered at the household level. All specifications include a full set of interactions between the principal components of the genetic data and the High SES dummy. This explains the large coefficients on High SES dummy in those specifications.

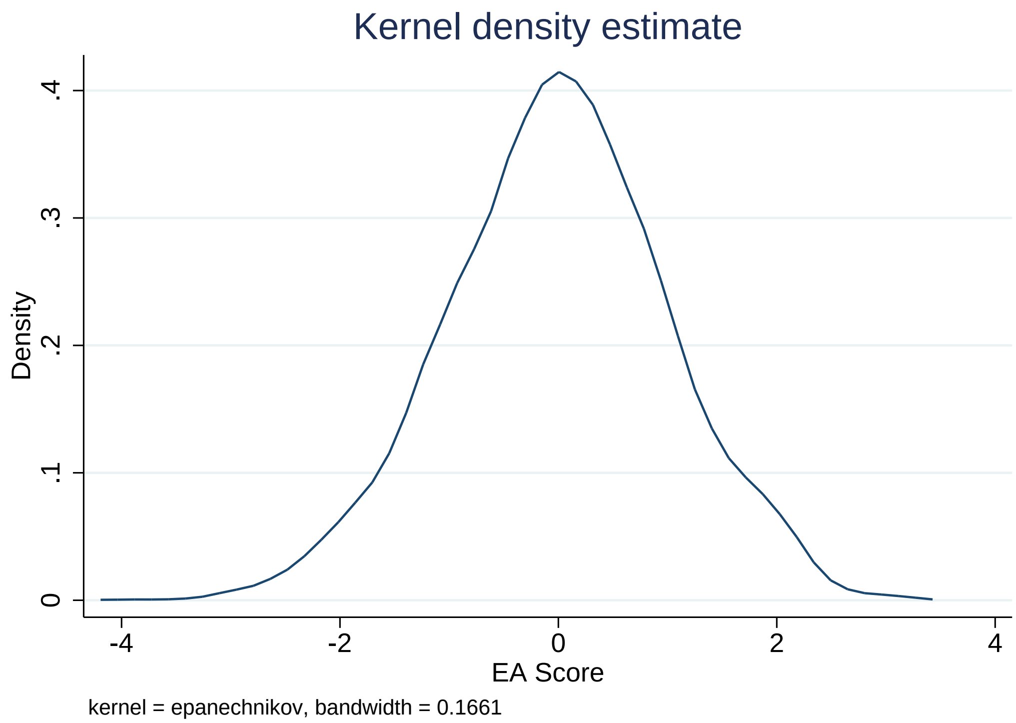

Figure 1: *Notes*: EA Score Distribution among HRS Individuals.

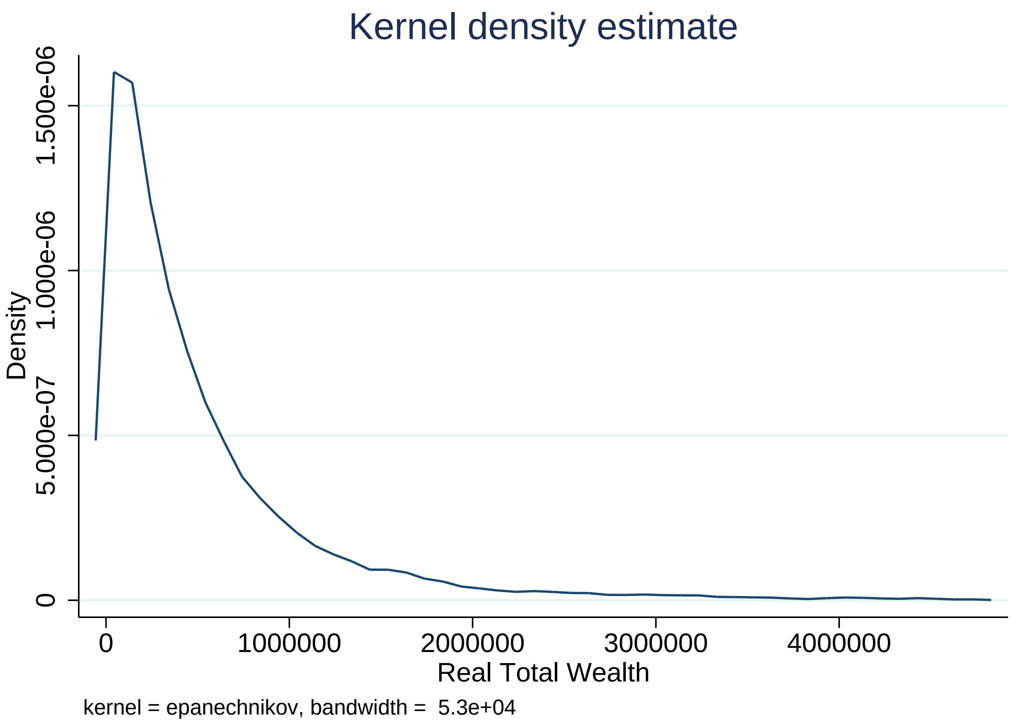

Figure 2: *Notes*: Wealth Distribution among HRS Individuals.

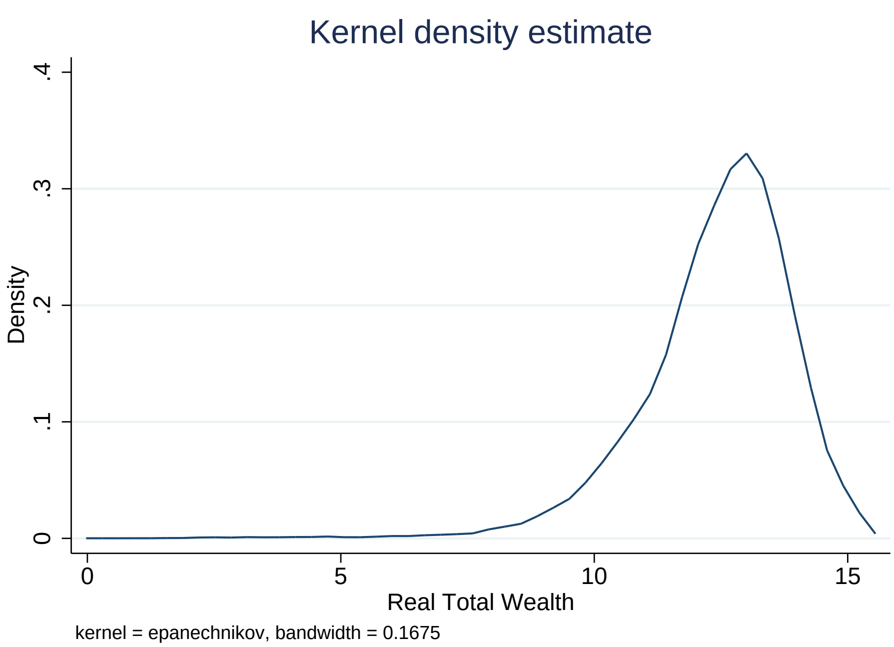

Figure 3: *Notes*: Log Wealth Distribution among HRS Individuals.

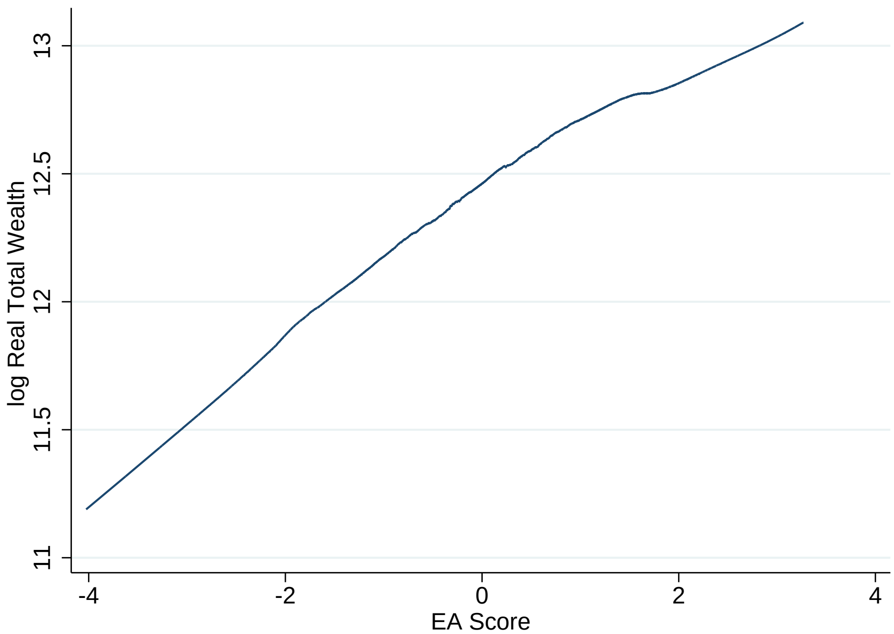

Figure 4: *Notes*: EA Score and Wealth among HRS Individuals.

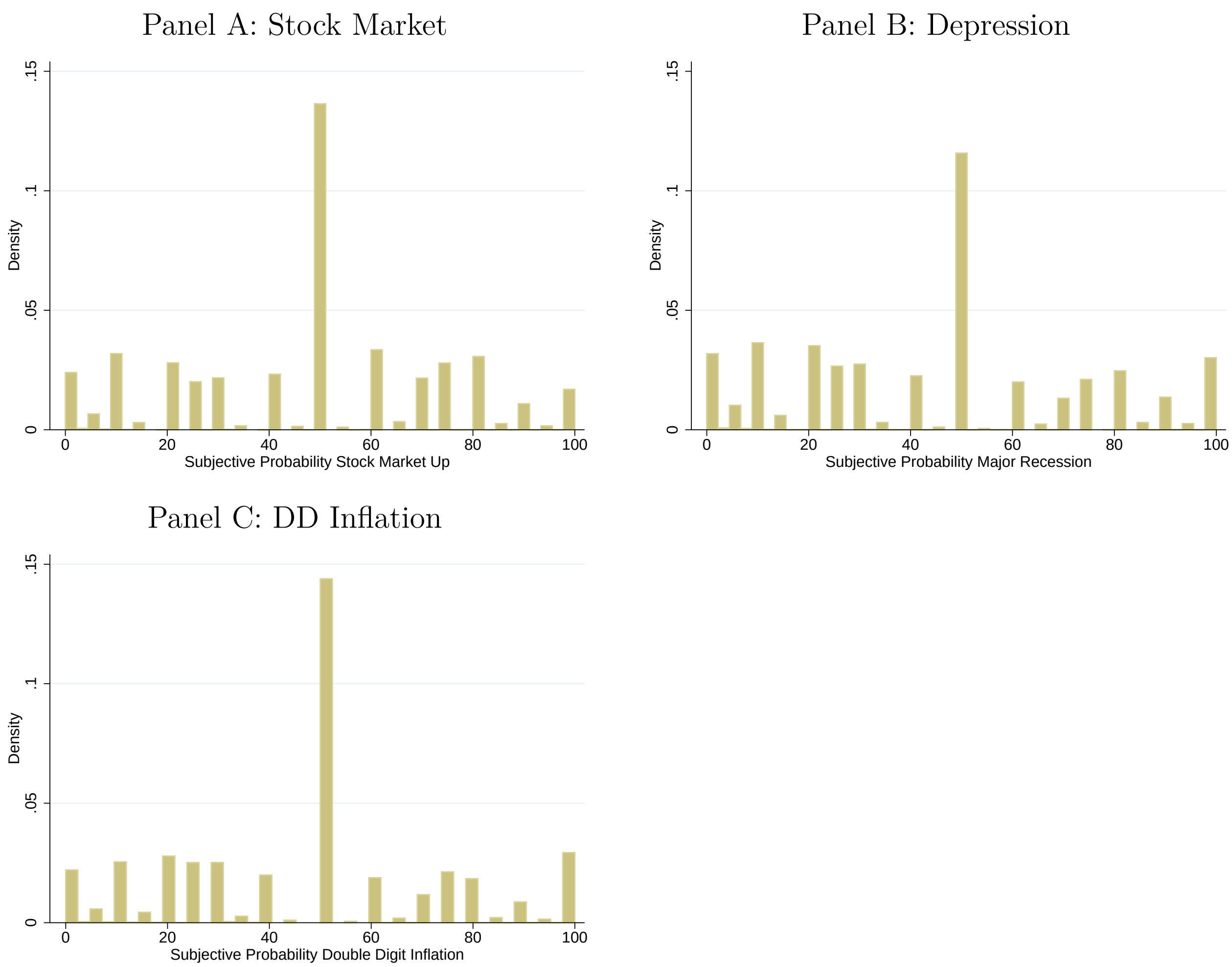

Figure 5: *Notes*: Distributions of Subjective Beliefs.

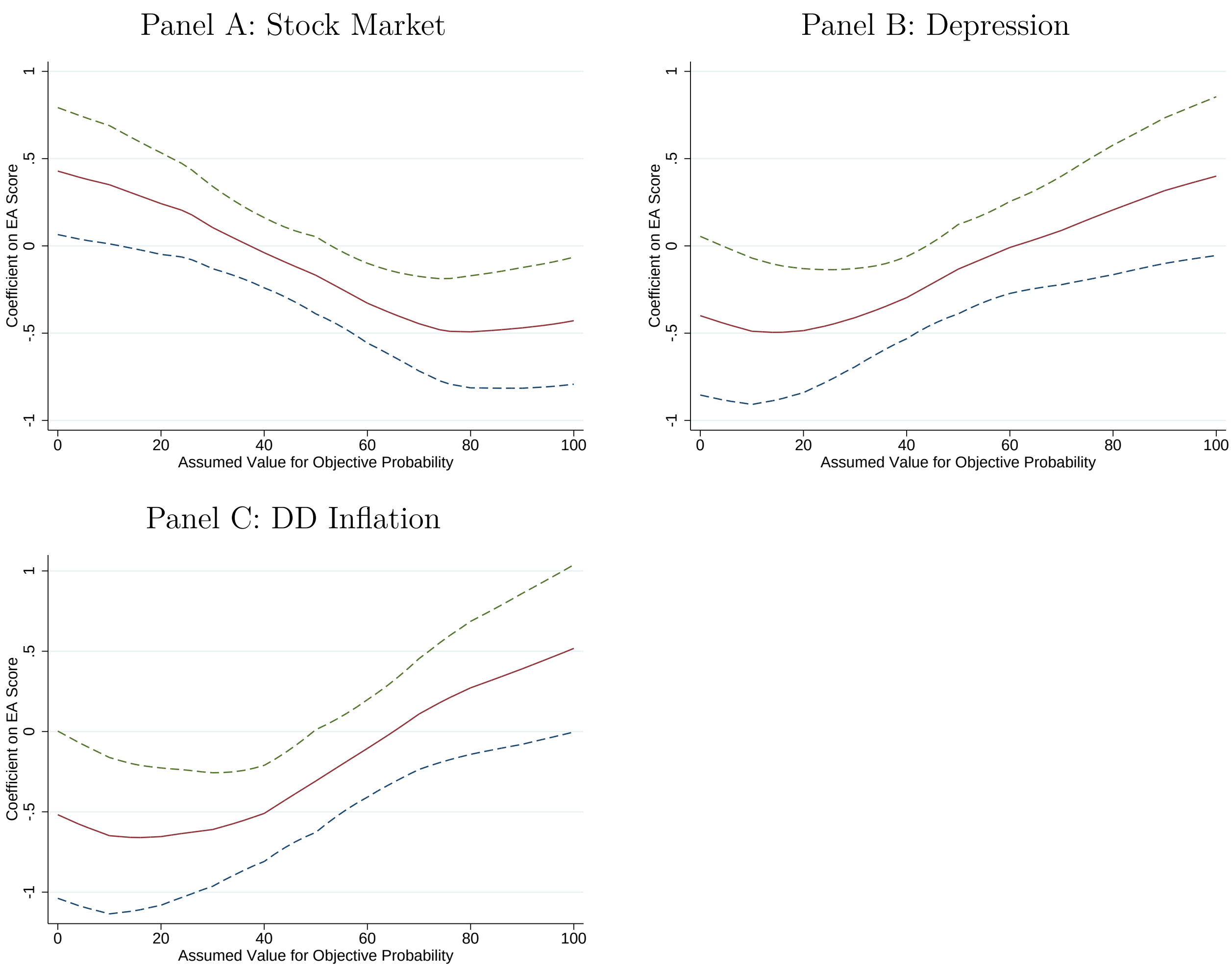

Figure 6: *Notes*: EA Score Coefficients for Alternative Values of Objective Beliefs.

Online Appendix:

"Genetic Ability, Wealth, and Financial Decision-Making"

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

A Additional Details on GWAS and Construction of the EA Score

What follows is nearly identical to the genetic data appendix in an earlier paper, Papageorge and Thom (2016), which uses the same genetic score used in the current paper. We reprint the appendix here solely for the reader's convenience In this appendix, we provide a brief introduction to molecular genetics and the kinds of genetic data that we use in this study. We repeat some portions of Section 2 so that this appendix can provide a self-contained introduction to GWAS and the EA score used in our analysis. First, we describe some basic features of the human genome. Next, we discuss how statistical gene-discovery projects can produce scores that are useful for the prediction of economic outcomes such as educational attainment. We highlight how recent advances permit credible and replicable inference.

The human genome consists of approximately 3 billion nucleotide base pairs spread out over 23 chromosomes. Each individual possesses two copies of each chromosome, one from each parent. A gene is a subsequence of base pairs within a chromosome. On average, each gene is made up of over 100,000 base pairs. Each base pair can either be an adenine-thymine (AT) pair, or a guanine-cytosine (GC) pair. Thus, the human genome can be thought of as a series of 3 billion genetic addresses, each of which can contain one of two nucleotide pairs.

A particular location in the genome can be referred to by a name (e.g. rs7937), which indicates its position in the genome. At the vast majority of such locations (about 99%), there is no variation in the observed nucleotide pair across humans or across chromosomes within a human. A single-nucleotide polymorphism (SNP) exists when there are differences in the nucleotide pair present at a particular location on the genome. An allele refers to one of the variants that may be present at a particular SNP. If AT is more commonly found at a particular SNP, it is referred to as the major allele, and then GC is referred to as the minor allele.

A traditional approach to the discovery of gene-behavior associations rests on examining *candidate genes*. Under this paradigm, researchers use some knowledge of the relevant biological processes to suggest places in the genome that might contain SNPs associated with a particular outcome. Unfortunately, this approach to identifying gene-economic outcomes has also generated a large number of reported associations that have failed to replicate outside of their discovery samples. This problem has been so widespread that an editorial statement from the journal *Behavior Genetics* stated that "The literature on candidate gene associations is full of reports that have not stood up to rigorous replication," and that "it now seems likely that many of the published findings of the last decade are wrong or misleading and have not contributed to real advances in knowledge," (Hewitt, 2012). This pattern has emerged, in part, because traditional candidate gene studies have been severely underpowered to detect real genetic effects. Sample sizes in general have been too small relative to the true effect sizes of individual SNPs, making it likely that statistically significant associations are the result of chance. This problem is exacerbated when studies search over many candidate genes, creating a multiple hypothesis testing problem that increases the likelihood of finding false positive results (Benjamin et al., 2012).

An alternative to candidate genes is an approach called a genome-wide association study (GWAS). Under the GWAS methodology, researchers scan the entire genome for SNPs that are associated with a particular phenotype (trait or outcome), but adopt strong measures to deal with multiple hypothesis-testing. For a particular outcome of interest, y_i, and for a set of observed SNPs, $\{SNP_{ij}\}_{j=1}^{N^J}$, a GWAS study proceeds by obtaining estimates of N^J separate regressions of the form:

$$y_i = \mu X_i' + \beta_j SNP_{ij} + \epsilon_{ij} \tag{1}$$

Here SNP_{ij} measures the number of copies of a reference allele possessed by individual i for SNP j. For example, if the reference allele at SNP j is AT, then SNP_{ij} could take the values 0, 1, or 2. The maximum value of 2 reflects the fact that an individual can have at most two copies of the reference allele — one on each inherited chromatid. Additionally, X_i is a vector of controls, including principal components of the genetic variables $\{SNP_{ij}\}_{j=1}^{N^J}$. Principal components of the genetic data are added to control for population stratification (Price et al., 2006; Benjamin et al., 2012). For example, it could be that SNP_{ij} is correlated with a particular ethnicity or ancestry group. Failure to control for the principal components could generate observed SNP-phenotype relationships that reflect the influence of broader ethnic differences rather than the influence of a particular genetic marker.

After obtaining estimates for all N^J versions of equation (1), those estimated coefficients $\widehat{\beta}_j$ with sufficiently small p-values are said to reflect relationships that are genome-wide significant. Given the huge number of regressions run under this methodology, the significance thresholds in modern GWAS are typically very strict. A conventional threshold is 5×10^{-8}. This approach has become popular and as a consequence of its stringency requirements, has led to the discovery of a number of credible genetic associations. For example, the well-known FTO gene for obesity was discovered through a GWAS, despite the lack of any existing biology that would have suggested it as a candidate gene (Benjamin et al., 2012).

Existing work has demonstrated the importance of credibly identified SNPs for several economic outcomes. These SNPs either directly emerged from a GWAS, or were candidate genes that were validated by later GWAS results. An established literature documents a number of credible genetic associations with smoking behaviors (Bierut, 2010; Thorgeirsson et al., 2010). Fletcher (2012) demonstrates that a SNP associated with smoking intensity also appears to moderate the effect of tobacco taxes. More closely related to our work, another set of studies suggests indirect linkages between genetic variants and human capital. For example, Fletcher and Lehrer (2011) use a set of SNPs associated with health outcomes to provide exogenous within-family variation to estimate a causal relationship between health and education. Finally, Thompson (2014) shows that a variant associated with the MAOA gene appears to moderate the relationship between income and education.

Recent work using GWAS has discovered some of the first direct associations between specific SNPs and education. Rietveld et al. (2013) identified three SNPs (rs9320913, rs11584700, rs4851266) attaining genome-wide significance in a GWAS for educational attainment. Follow-up work by the same team (the Social Science and Genetics Consortium) has recently extended the Rietveld et al. (2013) study to perform an educational attainment GWAS with a sample size of 293,723. This follow-up study, Okbay et al. (2016), has discovered 74 SNPs that attain genome-wide significance. We build our analysis here on the gene-education associations found in this follow-up study.

One common technique adopted in the GWAS literature is to take observed SNPs and the estimated GWAS coefficients (the $\widehat{\beta}_j$) and aggregate them into a polygenic score that can be used for prediction. Typically these scores take the following form:

$$PGS_i = \sum_j \widetilde{\beta}_j SNP_{ij} \tag{2}$$

where $\widetilde{\beta}_j$ is some transformation of the underlying GWAS coefficients. The $\widehat{\beta}_j$ estimates are typically corrected to account for correlation between SNPs and prevent over or under prediction. The follow up study Okbay et al. (2016) combines all genotyped SNPs into a polygenic score that attains a predictive power of up to 3.85% of the variation in educational attainment.[37] In our study, we use SNP weights $\widehat{\beta}_j$ that have been adjusted using a technique called LD Pred (Vilhjalmsson, 2015), and applied to the genetic data in the HRS.[38] We refer

[37]We note as well that the polygenic score that we use in this study combines all SNPs analyzed in Okbay et al. (2016), not just those reaching genome-wide significance. As noted in Okbay et al. (2016), this maximizes the predictive power out of sample.

[38]We would like to especially thank Aysu Okbay, a member of the Social Science and Genetics Consortium,

to the polygenic score created using these weights as the *EA score*, where "EA" stands for "educational attainment". We refer to it this way since other polygenic scores exist which capture genetic variation explaining different outcomes.

B Data Issues

This appendix provides details on the construction of our wealth data and our measurement of stock market participation. Our data are largely constructed from the RAND wealth and income files. The RAND files are carefully cleaned and consistently coded by RAND Corportation 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.

B.1 Wealth in Retirement 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.

for graciously generating and sharing this score with us.

B.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.[39] Specifically, we calculate the present value of retirement income, P_t, as:

$$P_t = Y_t \sum_{s=1}^{T-t-1} \frac{\prod_{u=1}^{s} p_{t+u}}{R}, \tag{3}$$

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.

B.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

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

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.[40] 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. 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. This means our stock market participation variable does not include stock ownership in dormant plans. The stock market participation variable is determined only by information in the assets and income section of the data, which comprises only stock and stock mutual funds as well as the stock allocation in IRA and Keogh accounts.

C Robustness Checks and Additional Results

This appendix contains a series of robustness checks and additional results not included in the main text. Section C.1 presents estimates of our primary specifications using alternate definitions of household wealth, different rules for sample inclusion, and additional control variables. Section C.2 contains results using the consumption data available in the RAND release of the Consumption and Activities Mail Survey (CAMS) supplement to the HRS.

C.1 Robustness of the Gene-Wealth Gradient

C.1.1 Alternate Definitions of Wealth

Here we estimate alternate specifications of our basic regressions to test the robustness of the relationship between household wealth and the EA score. We replicate five key results from Tables 5 and 13 by regressing the log of household wealth on our basic control set and additional covariates that may explain the gene-wealth gradient. The panels of Table S1 repeat this exercise using four different definitions of household wealth: total wealth, total wealth excluding housing, total wealth excluding housing and pensions, and total wealth excluding business wealth. In all cases, the dependent variable is the log of the relevant

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

household wealth measure.

In each successive column, we add to the set of covariates. Column (1) starts with our baseline control set, used in Column (1) of Table 5, which includes the respondent's education (years of schooling and a full set of degree dummies), and controls for mother's and father's education. Column (2) adds average log household income. Column (3) adds two bequest variables discussed in the main text (Column (3) of Table 5). Column (4) adds an indicator variable for having owned a business. Column (5) adds the full set of financial decision-making and beliefs variables used in Table 13. The sample is defined as in the main text and varies across specifications since the exclusion of some assets generates negative wealth values that are dropped when taking logs. Moreover, as in Table 5, we keep the sample constant across columns to allow for meaningful comparisons.

Comparing the Column (1) estimates across the four panels in Table S1, we consistently find that a one standard deviation increase in the EA score is associated with 11 to 13 percent higher total wealth, regardless of how wealth is measured. One exception occurs when we exclude both housing and pension wealth (Panel C), as the estimate suggests that a one-standard deviation increase in the EA score is associated with 25 percent higher wealth. This larger coefficient is sensible given our findings that pension wealth is largely independent of the EA score.

Controls for income, bequests, business ownership, and financial decision-making all reduce the size of the coefficient estimate on the EA score when added to the regression. Across specifications, we find that approximately one fifth of the Column (1) relationship between the EA score and wealth is explained by income, bequests and business ownership and that up to an additional one fifth is explained by the full suite of financial decision-making variables.

C.1.2 Alternate Sample Definitions

In Table S2, we repeat the analyses presented in Table S1, but assess robustness to changes in the sample. In our main text results, we do not restrict the sample by age. This raises concerns that selection bias influences our results if the EA score is associated with mortality. In particular, if the EA score is negatively associated with mortality, then positively selected survivors might be disproportionately represented among the low EA score observations in our sample. Panel A of Table S2 presents estimates of our specifications using only person-year observations on individuals aged 55-75. When restricting to this sub-sample, our results are qualitatively similar to our baseline results: there is a substantial gene-wealth gradient that is partially explained by income, bequests, business ownership, and financial-decision making.

Our baseline results restrict the sample to households composed of retired individuals, since we cannot credibly estimate the present discounted value of defined benefit pensions or Social Security payments for non-retirees. In Panel B, we relax this restriction and include all households regardless of age or retirement status. This substantially increases our sample sizes, but does not change our qualitative results.

C.1.3 Alternate Control Variables

Lifetime income represents an important potential mechanism linking the EA score and household wealth. We control for household income histories in Table 5 and elsewhere using the average of the log household labor income observed in the HRS. Although this average is strongly linked to household wealth in retirement, it may not offer a sufficient proxy for lifetime flows. Here we explore whether our basic results are robust to some alternate specifications. For comparison, Panel A of Table S3 presents our basic results using the average of the log of household income, which are identical to Panel A in Table S1. In Panel B of Table S3, we use the maximum of log household income instead of the average. Using the maximum instead of the average results in very similar estimates.

Our approach to controlling for income may also fail to capture important non-linearities in the relationship between income and wealth. To address this, we adopt a more flexible approach by calculating the quintiles of our two summary measures (average and max log income) and creating dummy variables indicating inclusion in the different quintile groups. In Panel A of Table S4, we control for income by including the quintile dummies for average log household income. Panel B repeats the same exercise using the quintile dummies for max log household income. In both panels, we find similar results that are quite consistent with our basic findings. Comparing Columns (1) and (2) in Table S4, it is interesting to note that controlling for the income quintiles does reduce the coefficient on the EA score. While these results suggest that there are non-linearities in the relationship between income and wealth, Table S4 again reaffirms our basic results: income, bequests, and business ownership explain approximately one quarter of the genetic gradient in wealth, with financial decision-making variables accounting for an additional one fifth of the relationship.

In Table S5, we assess the robustness of our main results to the inclusion of additional variables that could potentially explain the gene-wealth gradient. The expanded control set in all Columns now includes the number of individuals in the household, the number of children ever born to the financial respondent, and the number of years since retirement. Although adding these extra controls does reduce the coefficient on the EA score, our basic results on the gene-wealth gradient, and the importance of various mechanisms, still hold after including these variables.

C.2 Consumption and Spending

Consumption and savings behaviors are important determinants of household wealth. The relationship between the EA score and wealth could potentially operate through a household's saving rate. Unfortunately, the main waves of Health and Retirement Study lack the detailed consumption data that would be necessary to calculate either i) a savings rate for non-retired households, or ii) the ratio of consumption to wealth for retired households. Consumption and expenditure data are available in a supplement to the HRS: the Consumption and Activities Mail Survey (CAMS). Unfortunately, the CAMS is administered during non-survey years for the HRS (odd calendar years 2001, 2003, etc.), making it impossible to combine HRS wealth or income data with the consumption data to construct the saving rate or consumption-wealth ratio for a particular year. As an alternate approach, we combine consumption data from year $t+1$ with wealth data from year t to construct an approximate consumption to wealth ratio for year t: $\frac{C_{t+1}}{W_t}$. Our measure of consumption, C_{t+1}, comes from the RAND release of the CAMS data, which includes an aggregated total household consumption variable. The RAND data also includes a measure of total household expenditures, E_{t+1}, which we use to create an expenditure to wealth ratio, $\frac{C_{t+1}}{W_t}$. The consumption and expenditure measures differ in their treatment of spending on durable consumption goods.

Panel A of Table S6 presents estimates of a regression of the consumption to wealth ratio on the EA score and our standard set of controls (see Column (1) of Table 5). Panel B repeats this exercise using the expenditure to wealth ratio. In both cases we restrict the sample to households with ratios between 0 and 1. In Column (1), we find no statistically significant association between the EA score and the consumption ratio. In Column (2), we continue to find no statistically significant relationship after we include the log of total wealth as a control variable. We note that the consumption data are missing for a substantial fraction of households, leading to sample sizes that are much smaller than our main specifications. Since the consumption data come from a supplement, we cannot perform these exercises on our full sample. In Column (3), we expand the sample to include all households regardless of retirement status. We find a statistically significant, negative relationship between the EA score and the consumption-wealth ratio. Such a pattern could arise if individuals with higher EA scores are more likely to save, or are less likely to draw down their assets in retirement. However, in Column (4), we find no relationship between the EA score and the consumption ratio once we control for the log of household wealth. This suggests that the relationship between the score and the consumption wealth ratio, operates through a positive association between the EA score and wealth, not a relationship with consumption conditional on wealth. In Panel B of Table S6, we find exactly the same results if we use the expenditure wealth ratio instead of the consumption ratio. An alternate exercise would involve using household income and expenditure data for year t to construct a saving rate: $\frac{Y_t - Exp_{t+1}}{Y_t}$ for non-retired households. In results available upon request, we find no statistically significant association between the EA score and the saving rate. However, the sample size for this exercise is much smaller than our other specifications ($< 2,000$), so we may be underpowered to detect a relationship.

Given the limitations discussed earlier, the HRS data is not well suited to the analysis of saving behavior. With the data that are available, we fail to find evidence of a relationship between the EA score and consumption that might explain the genetic gradient in wealth. This accords with findings in Cronqvist and Siegel (2015), who show that, although there is a strong genetic basis for savings, education does not appear to be a mechanism explaining it. As we explain in the text, a genetic basis for wealth could be explained by two distinct pathways, one that works through self control and savings and the other — the focus of our study — that operates through education and financial decision-making.

Appendix Table S1: Robustness: Alternate Definitions of Wealth

Dep. Var: **log Tot. Wealth**	(1)	(2)	(3)	(4)	(5)
Panel A: Total Wealth					
EA Score	0.121***	0.114***	0.100***	0.090***	0.072***
	(0.028)	(0.027)	(0.027)	(0.027)	(0.025)
Obs.	7,599	7,599	7,599	7,599	7,599
R^2	0.277	0.330	0.345	0.351	0.393
Panel B: Exclude Housing					
EA Score	0.125***	0.117***	0.103***	0.094***	0.076***
	(0.029)	(0.028)	(0.028)	(0.028)	(0.027)
Obs.	7,528	7,528	7,528	7,528	7,528
R^2	0.291	0.342	0.354	0.359	0.396
Panel C: Exclude Housing and Ret. Wealth					
EA Score	0.245***	0.237***	0.208***	0.184***	0.151***
	(0.051)	(0.050)	(0.049)	(0.049)	(0.047)
Obs.	6,743	6,743	6,743	6,743	6,743
R^2	0.218	0.254	0.273	0.283	0.318
Panel D: Exclude Business Wealth					
EA Score	0.110***	0.103***	0.089***	0.082***	0.064**
	(0.028)	(0.026)	(0.026)	(0.026)	(0.025)
Obs.	7,599	7,599	7,599	7,599	7,599
R^2	0.282	0.335	0.350	0.355	0.396

Notes: Significance stars ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. The dependent variable in all specifications is the log of total wealth. All regressions include the standard set of controls outlined in the Notes to Table 4, as well as controls for the respondent's education (years of schooling and a fully set of degree dummies), and controls for mother's and father's education. Column (2) adds average log household income as a control. Column (3) adds two bequest variables. Column (4) adds a variables indicating business ownership. Column (5) adds variables pertaining to financial decision-making. The wealth measure changes across Panels A-D. Wealth in Panel A is the same as in the main text. In Panel B, housing wealth is excluded. In Panel C, housing and retirement wealth is excluded. In Panel D, wealth from businesses owned by the household is excluded. In all regressions, standard errors are clustered at the household level. To allow for comparability of coefficients across specifications, in each panel, the sample in all specifications is restricted to households with non-missing observations on the full set of explanatory variables used in the final specification in Column (5). We use data on all household-year observations where each member of the household is either not working for pay or is retired.

Appendix Table S2: Robustness: Alternate Samples

Dep. Var: log Tot. Wealth	(1)	(2)	(3)	(4)	(5)
Panel A: Financial Resp. Aged 55-75					
EA Score	0.103***	0.092***	0.078***	0.069**	0.053**
	(0.029)	(0.028)	(0.028)	(0.027)	(0.026)
Obs.	6,251	6,251	6,251	6,251	6,251
R^2	0.246	0.311	0.327	0.334	0.376
Panel B: All Households (including the non-retirees)					
EA Score	0.105***	0.093***	0.083***	0.077***	0.065***
	(0.022)	(0.021)	(0.020)	(0.020)	(0.019)
Obs.	16,088	16,088	16,088	16,088	16,088
R^2	0.202	0.248	0.264	0.275	0.309

Notes: Significance stars ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. The dependent variable in all specifications is the log of total wealth. All regressions include the standard set of controls outlined in the Notes to Table 4, as well as controls for the respondent's education (years of schooling and a fully set of degree dummies), and controls for mother's and father's education. Column (2) adds average log household income as a control. Column (3) adds two bequest variables. Column (4) adds a variables indicating business ownership. Column (5) adds variables pertaining to financial decision-making. Panel A restricts our basic sample to those household-year observations in which the age of the financial respondent falls in the range 55-75. We use data on all household-year observations where no individual in the household is un-retired and working for pay. In Panel B, we include all age groups, and do not restrict the sample based on retirement or work status. In all regressions, standard errors are clustered at the household level. For all specifications, the sample includes non-retirees. To allow for comparability of coefficients across specifications, in each panel, the sample in all specifications is restricted to households with non-missing observations on the full set of explanatory variables used in the final specification in Column (5).

Appendix Table S3: Robustness: Alternative Income Controls (I)

Dep. Var: log Tot. Wealth	(1)	(2)	(3)	(4)	(5)
Panel A: log Household Income					
EA Score	0.121***	0.114***	0.100***	0.090***	0.072***
	(0.028)	(0.027)	(0.027)	(0.027)	(0.025)
log income		0.385***	0.371***	0.377***	0.334***
		(0.037)	(0.037)	(0.038)	(0.035)
Obs.	7,599	7,599	7,599	7,599	7,599
R^2	0.277	0.330	0.345	0.351	0.393
Panel B: log Max. Household Income					
EA Score	0.121***	0.110***	0.096***	0.089***	0.071***
	(0.028)	(0.027)	(0.027)	(0.027)	(0.026)
log max. income		0.337***	0.325***	0.319***	0.278***
		(0.036)	(0.036)	(0.036)	(0.033)
Obs.	7,599	7,599	7,599	7,599	7,599
R^2	0.277	0.323	0.339	0.342	0.385

Notes: Significance stars ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. The dependent variable in all specifications is the log of total wealth. All regressions include the standard set of controls outlined in the Notes to Table 4, as well as controls for the respondent's education (years of schooling and a fully set of degree dummies), and controls for mother's and father's education. Column (2) adds average log household income as a control. Column (3) adds two bequest variables. Column (4) adds a variables indicating business ownership. Column (5) adds variables pertaining to financial decision-making. Panel A controls for household income with the average of log household income in the HRS. In Panel B, we instead control for income using maximum log annual household income. In all regressions, standard errors are clustered at the household level. To allow for comparability of coefficients across specifications, in each panel, the sample in all specifications is restricted to households with non-missing observations on the full set of explanatory variables used in the final specification in Column (5). We use data on all household-year observations where each member of the household is either not working for pay or is retired.

Appendix Table S4: Robustness: Alternative Income Controls (II)

Dep. Var: log **Tot. Wealth**	(1)	(2)	(3)	(4)	(5)
Panel A: Controlling for Quintiles of Average log Household Income					
EA Score	0.121***	0.108***	0.094***	0.085***	0.069***
	(0.028)	(0.027)	(0.027)	(0.026)	(0.025)
Quintile 2		0.077	0.081	0.095	0.076
		(0.085)	(0.084)	(0.083)	(0.080)
Quintile 3		0.413***	0.419***	0.446***	0.452***
		(0.087)	(0.087)	(0.087)	(0.085)
Quintile 4		0.713***	0.676***	0.713***	0.652***
		(0.083)	(0.082)	(0.083)	(0.080)
Quintile 5		1.161***	1.135***	1.156***	1.026***
		(0.087)	(0.086)	(0.086)	(0.084)
Obs.	7,599	7,599	7,599	7,599	7,599
R^2	0.277	0.346	0.360	0.367	0.406
Panel B: Controlling for Quintiles of Maximum log Household Income					
EA Score	0.121***	0.098***	0.085***	0.079***	0.064**
	(0.028)	(0.027)	(0.027)	(0.026)	(0.025)
Quintile 2		0.167*	0.189**	0.196**	0.192**
		(0.087)	(0.087)	(0.086)	(0.083)
Quintile 3		0.564***	0.554***	0.566***	0.542***
		(0.085)	(0.084)	(0.085)	(0.081)
Quintile 4		0.762***	0.735***	0.739***	0.677***
		(0.092)	(0.091)	(0.091)	(0.089)
Quintile 5		1.224***	1.202***	1.189***	1.044***
		(0.092)	(0.091)	(0.091)	(0.088)
Obs.	7,599	7,599	7,599	7,599	7,599
R^2	0.277	0.345	0.359	0.362	0.401

Notes: Significance stars ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. The dependent variable in all specifications is the log of total wealth. All regressions include the standard set of controls outlined in the Notes to Table 4, as well as controls for the respondent's education (years of schooling and a fully set of degree dummies), and controls for mother's and father's education. Column (2) adds average log household income as a control. Column (3) adds two bequest variables. Column (4) adds a variables indicating business ownership. Column (5) adds variables pertaining to financial decision-making. In Panel A, quintiles of average log income are used in place of average log income. In Panel B, quintiles of maximum observed household log income is used in place of average log income. In all regressions, standard errors are clustered at the household level. To allow for comparability of coefficients across specifications, in each panel, the sample in all specifications is restricted to households with non-missing observations on the full set of explanatory variables used in the final specification in Column (5). We use data on all household-year observations where each member of the household is either not working for pay or is retired.

Appendix Table S5: Robustness: Expanded Set of Control Variables

Dep. Var: log Tot. Wealth	(1)	(2)	(3)	(4)	(5)
EA Score	0.111***	0.105***	0.093***	0.086***	0.072***
	(0.027)	(0.026)	(0.026)	(0.026)	(0.025)
Obs.	7,363	7,363	7,363	7,363	7,363
R^2	0.348	0.387	0.399	0.402	0.435

Notes: Significance stars ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. The dependent variable in all specifications is the log of total wealth. All regressions include the standard set of controls outlined in the Notes to Table 4, as well as controls for the respondent's education (years of schooling and a fully set of degree dummies), and controls for mother's and father's education. In addition, all specifications include years since retirement, the number of children of the financial respondent, and the number of individuals in the household. Column (2) adds average log household income as a control. Column (3) adds two bequest variables. Column (4) adds a variables indicating business ownership. Column (5) adds variables pertaining to financial decision-making. In all regressions, standard errors are clustered at the household level. To allow for comparability of coefficients across specifications, in each panel, the sample in all specifications is restricted to households with non-missing observations on the full set of explanatory variables used in the final specification in Column (5). We use data on all household-year observations where no individual in the household is un-retired and working for pay.

Appendix Table S6: Robustness: Consumption

	(1)	(2)	(3)	(4)
Panel A: Dep. Var: Consumption-Wealth Ratio				
EA Score	-0.008	0.001	-0.008**	0.000
	(0.005)	(0.003)	(0.004)	(0.002)
Control for Wealth	No	Yes	No	Yes
Obs.	3,250	3,250	5,018	5,018
R^2	0.175	0.625	0.135	0.621
Panel A: Dep. Var: Spending-Wealth Ratio				
EA Score	-0.008	0.001	-0.010**	-0.000
	(0.005)	(0.003)	(0.004)	(0.003)
Control for Wealth	No	Yes	No	Yes
Obs.	3,259	3,259	5,009	5,009
R^2	0.166	0.615	0.131	0.599

Notes: Significance stars ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. The dependent variable in Panel A is the ratio of aggregate consumption in year $t+1$ to wealth in year t. The dependent variable in Panel B is a similarly constructed ratio of spending to wealth. Columns (1) - (2) use person-year observations that meet our basic sample selection criteria from Table 4. Column (1) includes our basic control set, while Column (2) adds the log of total wealth as a control. Columns (3)-(4) repeat this exercise, but expand the sample to include all households regardless of retirement status.