

Genetic Endowments and Wealth Inequality

Daniel Barth

University of Southern California

Nicholas W. Papageorge

*Johns Hopkins University, Institute of Labor Economics, and National Bureau
of Economic Research*

Kevin Thom

University of Wisconsin–Milwaukee

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

I. Introduction

Wealth inequality in the United States and many other countries is substantial and growing (Saez and Zucman 2014; Jones 2015). Income

We thank Aysu Okbay for constructing and sharing some of the polygenic scores used for Health and Retirement Study respondents. We are also grateful for helpful comments

Electronically published February 28, 2020

[*Journal of Political Economy*, 2020, vol. 128, no. 4]

© 2020 by The University of Chicago. All rights reserved. 0022-3808/2020/12804-0008\$10.00

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

In this paper, we explore the relationship between genetic factors and household wealth. Our measure of genetic variation is a linear index of genetic markers, or polygenic score, associated with years of schooling. Polygenic scores have been constructed to predict a number of outcomes, and the score we use is specific to educational attainment. We demonstrate an economically large and statistically significant empirical relationship between the polygenic score and household wealth at retirement. We also document relationships between the score and a number of underlying factors relevant for wealth accumulation, including financial decisions and beliefs about the macroeconomy. Our results suggest that the genetic transmission of traits related to wealth may be one component of the intergenerational persistence of wealth (Charles and Hurst 2003; De Nardi 2004; Black, Devereux, and Salvanes 2005; Benhabib,

from Robert Barbera, Daniel Belsky, Lee Benham, Jess Benhabib, Daniel Benjamin, Daniel Bennett, Alberto Bisin, Christopher Carroll, David Cesarini, Gabriella Conti, Stephanie DeLuca, Manasi Deshpande, Weili Ding, Benjamin Domingue, Steven Durlauf, Jon Faust, Titus Galama, Barton Hamilton, Bruce Hamilton, Joseph Hotz, Steven Lehrer, George-Levi Gayle, Robin Lumsdaine, Shelly Lundberg, Luigi Pistaferri, Robert Pollak, Paul Romer, Simone Schaner, Stephan Siegel, Matthew Shapiro, Dan Silverman, Jonathan Skinner, Rachel Thornton, Robert Topel, Jasmin Wertz, Robert Willis, Jonathan Wright, and Basit Zafar, along with seminar participants at the Center for Economic and Social Research; Clemson; City University of New York–Baruch College; Dartmouth; Duke; Johns Hopkins; Michigan; Penn State; Rochester; Stony Brook; University of California, Los Angeles; University of California, Santa Barbara; University of North Carolina–Chapel Hill; University of Wisconsin–Milwaukee; William and Mary; Bates White; the Inter-American Development Bank; the Bureau of Economic Analysis; the 2016 Human Capital and Economic Opportunity Global Working Group Conference on Genetics and Social Science; the Second Annual Empirical Microeconomics Conference at Arizona State University; the 2017 NBER Cohort Studies meetings; the 2017 North American summer meetings of the Econometric Society; the 2017 NBER Institute (Aging); and the 2017 Population Association of America Meetings. We acknowledge excellent research assistance from Andrew Gray, Emma Kalish, Oscar Volpe, and Matthew Zahn. Finally, the authors note that a previous version of this paper was circulated in 2017 with the title “Genetic Ability, Wealth and Financial Decision-Making.” The usual caveats apply. Research reported in this publication was supported by the National Institute on Aging of the National Institutes of Health under award RF1AG055654. The content is solely the responsibility of the authors and does not necessarily represent the official views of the National Institutes of Health. Data are provided as supplementary material online.

Bisin, and Zhu 2011). They also suggest that an understanding of the intergenerational transmission of economic outcomes that does not account for the role of genetics is likely to be incomplete, possibly overstating the importance of other factors such as parental investments and financial transfers.

We begin by establishing a robust relationship between household wealth in retirement and the average polygenic score within the household. A 1 standard deviation increase in the score is associated with a 25% increase in household wealth (approximately \$165,347 at the median wealth, in 2010 dollars). The relationship between the polygenic score and wealth is present across time and education groups. Measures of educational attainment, including years of education and completed degrees, explain over two-thirds of this relationship. Using detailed income data from the Social Security Administration (SSA) as well as self-reported labor earnings from the Health and Retirement Study (HRS), we find that labor income can explain less than half of the gene-wealth relationship that remains. After conditioning on lifetime income and household education, we find that a 1 standard deviation increase in the score is associated with a 5% increase in household wealth (approximately \$28,741 at the median).

Next, we explore additional mechanisms that may explain the gene-wealth gradient. Because individuals receive their genes from their parents, we first examine factors related to intergenerational transfers. We show that the polygenic score is positively related to parental education, which may proxy for transfers and advantageous family environments. We do not find a statistically significant relationship between higher scores and the probability of receiving an inheritance or with the size of the inheritance conditional on receiving one. The gene-wealth gradient remains economically large and statistically significant after controlling for both parental education and the size and incidence of inheritances.

We also consider savings behavior and portfolio choice as possible mechanisms through which genetic factors might operate. While the HRS is not well suited for a direct analysis of savings rates, we examine whether previously documented determinants of savings are associated with the polygenic score. We find that higher individual polygenic scores predict lower objective probabilities of death as well as subjective beliefs about mortality, which may motivate higher savings rates in anticipation of longer life spans.¹ We also document an association between an individual's polygenic score and measures of risk tolerance constructed from responses to hypothetical income and wealth gambles, which may affect both the savings rate and how savings are invested. This is consistent with previous

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

research suggesting a genetic basis for risk preferences (Cesarini et al. 2009). We find strong evidence that households with different scores differ in how they save. In particular, we find that higher-scoring households are more likely to invest in the stock market, and this appears to play a particularly important role in mediating the relationship between the score and wealth.

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

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

To explore this issue, our final set of results examines how the polygenic score interacts with a policy-relevant variable: pensions. Because defined-benefit pensions offer recipients a guaranteed stream of income without requiring them to make choices about contribution rates or asset composition, such plans should reduce differences in wealth that arise from skill in financial decision-making. We find that the gene-wealth gradient is over four times as large for the subset of households that do not participate in defined-benefit pension plans. This exercise is useful for two reasons. First,

it offers compelling support for the hypothesis that financial decisions may be a source of the gene-wealth gradient. Second, it also highlights a potentially important policy consideration. While more flexible plans such as 401(k) accounts grant individuals greater freedom in planning for retirement, they may also reduce the welfare of those who find it more difficult to navigate complex financial choices.

This study relates to the literature on endowments, economic traits, and household wealth. One strand of this work examines how various measures of “ability,” such as intelligence quotient or cognitive test scores, predict household wealth and similar outcomes (Lillard and Willis 2001; Grinblatt, Keloharju, and Linnainmaa 2011; Grinblatt et al. 2015).² However, parental investments and other environmental factors can directly affect test performance, making it difficult to use test scores to separate the effects of endowed traits from endogenous human capital investments. In contrast, genetic measures are predetermined if not exogenous. That is, while polygenic scores are correlated with environmental factors, they are not directly manipulated by environments and investments in the same way as test scores.

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

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

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

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

offer some of the richest data on household wealth and related behavioral traits.

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

II. Molecular Genetic Data and Economic Analysis

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

A. *The Human Genome*

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

Across the entire human genome, there are approximately 3 billion locations featuring nucleotide base pair molecules. However, differences across people in these base pairs is observed at less than 1% of these locations.⁵ Variation in the base pair molecules at a particular location is

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

referred to as a single-nucleotide polymorphism (SNP, pronounced “snip”). Because individuals inherit two sets of chromosomes—one from each parent—at each SNP an individual can have either two ATs, two GCs, or one AT and one GC. Genetic data thus most commonly take the form of a series of count variables indicating the number of copies of the reference molecule (ATs or GCs, depending on the location and conventions) possessed by an individual at each SNP: 0, 1, or 2. A central task in behavioral genetics involves determining which (if any) of these SNP variables are associated with behavioral outcomes.

*B. Genome-Wide Association Studies (GWASs)
and Polygenic Scores*

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

$$Y_{ij} = A_i + C_f + E_i. \quad (1)$$

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

While twins studies provide an estimate of how much genetic factors collectively matter for explaining variation in a given trait, they do not reveal which specific SNPs are relevant. By contrast, GWASs estimate associations between individual SNPs and outcomes of interest. A GWAS typically proceeds by gathering data on J observable SNPs, $\{\text{SNP}_{ij}\}_{j=1}^J$, and estimating J separate regressions similar to the following:

$$Y_i = \mu X_i' + \beta_j \text{SNP}_{ij} + \epsilon_{ij}, \quad (2)$$

where $\text{SNP}_{ij} \in \{0, 1, 2\}$ measures the number of ATs or GCs (again depending on convention) possessed by individual i for SNP j and X_i is a

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

vector of control variables. Separate regressions for each SNP are estimated because in practice, one typically has many more genotyped SNPs than observations in a discovery sample.

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

$$\text{PGS}_i = \sum_{j=1}^J \tilde{\beta}_j \text{SNP}_{i,j}, \quad (3)$$

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

As shown in equation (3), a polygenic score is simply a linear combination of SNPs and their effect sizes. While relatively few SNPs are likely to achieve genome-wide significance⁷—a stringent threshold for the statistical significance of a single β_j that accounts for multiple-hypothesis testing and other factors—many polygenic scores include all SNPs included in the GWAS. In the case of educational attainment, previous studies have shown that a score using all SNPs produces better out-of-sample prediction than polygenic scores that use only SNPs with genome-wide significance (Okbay et al. 2016). In the context of equation (1), the polygenic score can be thought of as the best SNP-based linear predictor of the common genetic component A_i .

⁷ Given the large number of regression equations being estimated, correction for multiple-hypothesis testing has been a key concern in this literature. For the purposes of determining whether an individual SNP-outcome association is statistically significant, the literature has adopted stringent p -value thresholds. A benchmark threshold for genome-wide significance is $p < 5 \times 10^{-8}$. Stringent thresholds were developed in part as a response to earlier methods used to measure gene-outcome associations using so-called candidate genes, which are genes that the researcher believes may be implicated in an outcome arising from knowledge of biological processes. This approach suffered from false positives due to an uncorrected multiple-hypothesis testing problem (Benjamin et al. 2012).

C. *The Educational Attainment (EA) Score*

GWASs have traditionally focused on medical or health-related outcomes, such as smoking (Bierut 2010; Thorgeirsson et al. 2010) and obesity (Locke et al. 2015). However, the increasing availability of genetic data has made it possible to perform well-powered GWASs for behavioral traits with more distant relationships to underlying biological mechanisms. In particular, a series of landmark studies have delivered the first GWAS associations between individual SNPs and educational attainment—specifically, years of schooling (Rietveld et al. 2013; Okbay et al. 2016; Lee et al. 2018). Existing work shows that polygenic scores for educational attainment based on these GWASs predict labor market outcomes, including earnings (Papa-george and Thom 2019), and other measures of adult success (Belsky et al. 2016), even after controlling for completed education.

In this paper, we study a polygenic score on the basis of the educational attainment GWAS results from Lee et al. (2018), which featured a discovery sample of over 1.1 million people.⁸ Importantly, HRS data are not used to estimate the GWAS associations $\{\hat{\beta}_j\}_{j=1}^J$ for this score, so every analysis in this study is an out-of-sample exercise.⁹

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

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

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

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

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

likely too simplistic and may lead to the mischaracterization of the EA score as solely capturing cognitive function.

D. Interpretational Issues

Several caveats apply to the interpretation of variation in polygenic scores and correlations between polygenic scores and outcomes. First, it is difficult to assign a causal interpretation to the estimated relationship between the score and the outcomes. In particular, variation in the polygenic score may reflect differences in environments or parental investments rather than differences in genetic factors across individuals. Parents provide their children not only with genetic material but also with the environments in which they are raised. It is therefore possible that higher polygenic scores could be associated with higher education and wealth largely through parental choices. We explore this point in greater detail when discussing our main findings.

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

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

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

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

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

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

III. The HRS Sample and Key Economic Variables

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

A. *Sample Construction*

The HRS is a longitudinal study that follows Americans over age 50 and their partners. Surveys began in 1992 and occur every 2 years. The HRS

¹³ As part of the genetic data release, the HRS calculates polygenic scores and principal components that are specific to European ancestry groups. The HRS defines individuals of European ancestry as “all self-reported non-Hispanic whites that had [principal component] loadings within \pm one standard deviations of the mean for eigenvectors 1 and 2 in the [principal components] analysis of all unrelated study subjects” (Ware et al. 2018, 4).

¹⁴ The authors write, “the African populations sampled are genetically predicted to be considerably shorter than all Europeans and minimally taller than East Asians, which contradicts empirical observations” (Martin et al. 2017, 7).

collected genetic samples from just under 20,000 individuals over the course of four waves (2006, 2008, 2010, 2012). Our sample includes only those genotyped in the 2006 and 2008 waves, since the polygenic score we use has not yet been constructed for the 2010 and 2012 waves.

Our main analysis sample includes all households with at least one individual classified as a genetic European by the HRS. We drop households in which any member self-identifies as nonwhite. We further restrict our sample to include only retired households in 1996, 1998, and 2002–10.¹⁵ We also include only those households with one or two members and exclude households where both members are of the same sex because such households may have faced unique circumstances during their primary wealth-accumulation years. Finally, to minimize selection bias related to mortality, we include only household-year observations in which both members are between 65 and 75 years old. Our restriction aims to balance concerns about measurement error in wealth with concerns about selection biases that arise if too many observations are excluded from the analysis. The resulting analytic sample includes 2,590 households and 5,701 household-year observations, with responses supplied for an average of 2.2 waves.

B. Education and Income

Table 1 provides summary statistics for key variables used in the main analyses. On average, the men in the sample were born 2 years before the women. While the mean years of education are similar for both men and women, the standard deviation is larger for men. Relatedly, men are more likely to have both high degree outcomes (college, master of arts [MA], and professional degrees) and low degree outcomes (no degree, General Educational Development [GED] degree).

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

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

TABLE 1
SUMMARY STATISTICS

Variable	Mean	Standard Deviation	Observations
Year of birth:			
Female	1935.10	5.59	2,369
Male	1933.04	5.76	2,015
Years of education:			
Female	12.67	2.30	2,369
Male	12.74	2.96	2,015
Highest degree:			
Female:			
No degree	.16	.37	2,369
GED	.04	.19	2,369
High school degree	.60	.49	2,369
Some college	.04	.19	2,369
College degree	.10	.30	2,369
MA	.05	.22	2,369
Professional degree	.01	.09	2,369
Male:			
No degree	.19	.39	2,015
GED	.06	.24	2,015
High school degree	.47	.50	2,015
Some college	.03	.18	2,015
College degree	.13	.34	2,015
MA	.08	.27	2,015
Professional degree	.04	.18	2,015
Household income (×\$1,000):			
Mean	2,315.95		2,377
Standard deviation	1,405.43		2,377
Average years top coded	12.67		2,377
25th percentile	1,287.80		2,377
50th percentile	2,255.30		2,377
75th percentile	3,082.30		2,377
Household wealth (×\$1,000):			
Mean	900.17		5,621
Standard deviation	1,411.22		5,621
10th percentile	168.74		5,621
25th percentile	303.82		5,621
50th percentile	593.64		5,621
75th percentile	1,031.48		5,621
90th percentile	1,706.83		5,621
Median, no housing	450.49		5,621
Median, no pensions	235.98		5,621
Median, no housing or pensions	92.00		5,621

NOTE.—Summary statistics for birth year, schooling, and highest degree completed are calculated separately for males and females. Income and wealth are computed at the household level. Additional statistics are found in tables S1–S6 (tables S1–S15 are available online).

and Hudson 2009, 29).¹⁶ The Respondent Cross-Year Summary Earnings provides annual MEF income totals for individuals over the period 1951–2013.

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

Our baseline income measure is the sum of all earned income in the MEF associated with a household for all available years through 2010, converted to 2010 dollars. This may include earnings from deceased spouses that are not directly observed in the HRS.¹⁷ Table 1 summarizes the distribution of lifetime household income. The median household earned a total of \$2.26 million. Lifetime income has a mean of just over \$2.3 million with a standard deviation of just over \$1.4 million.

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

C. *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 asked only in certain waves and only for plans associated with the current employer, and expected defined-benefit pension income is asked only of plans at the current employer. In some cases, such issues may be relatively unimportant. However, because this paper studies heterogeneity in wealth for elderly households, having a complete picture of retirement assets is of fundamental importance. While some data issues have no hope of being resolved, our sample comprises households for whom wealth data are most likely to be both accurate and comprehensive.

Our measure of total wealth is designed to encompass all components of household wealth. Our data include the present value of all pension, annuity, and social security income, which come from the RAND HRS income files, as well as the net value of housing (including primary and secondary residences as well as investment property), the net value of private businesses and vehicles, and all financial assets including cash, checking

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

accounts, savings accounts, certificates of deposit, stocks and stock mutual funds, bonds and bond mutual funds, trusts, and other financial assets, less the net value of nonhousing debt. Each of these are taken from the RAND HRS wealth files.¹⁸ Further, we include the account value of all defined-contribution retirement plans.¹⁹ We exclude the value of insurance policies from our wealth measure.²⁰ All monetary values are measured in 2010 dollars. Unless otherwise noted, we winsorize the log of real total household wealth at the 1st and 99th percentiles.

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

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

D. The EA Score in the HRS Sample

Since our unit of analysis is the household, we use the average EA score within households as our measure of genetic endowments. Hereafter, we use the term "EA score" to refer to the household average unless

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

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

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

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

E. Sample Selection

We highlight two possible sources of selection bias in our sample: (a) selection into genotyping and (b) selection on the basis of retirement

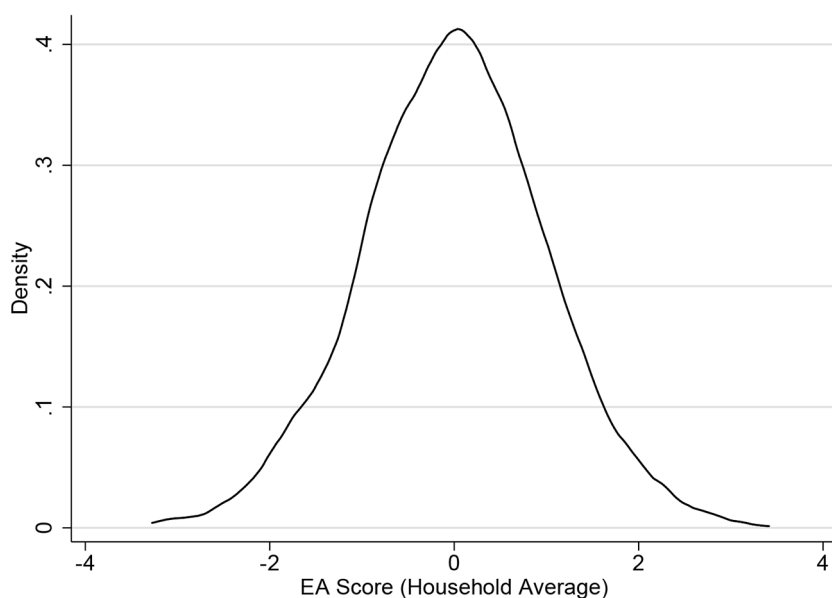


FIG. 1.—Distribution of household average EA score.

TABLE 2
HOUSEHOLD EA SCORE RELATED TO KEY ECONOMIC VARIABLES

	Q1 (1)	Q2 (2)	Q3 (3)	Q4 (4)	Q4 – Q1 (5)	Q4 – Q1 <i>p</i> -Value (6)
A. Average household EA score and individual variables:						
Female:						
Education	11.73	12.19	13.02	13.71	1.99	<.01
Father's education	8.66	8.99	9.82	10.63	1.97	<.01
Mother's education	9.34	9.48	10.37	10.62	1.28	<.01
Male:						
Education	11.58	12.23	13.17	13.96	2.38	<.01
Father's education	8.59	9.01	9.65	10.47	1.89	<.01
Mother's education	9.10	9.66	10.27	10.62	1.53	<.01
B. Average household EA score and household variables:						
Average household income (×\$1,000)	2,132.02	2,260.31	2,361.22	2,513.39	381.37	<.01
Average household wealth (×\$1,000)	603.87	771.27	909.93	1,082.24	478.36	<.01

NOTE.—This table relates the EA score to key economic variables. Columns 1–4 separate individuals into quartiles (Q1–Q4) of the individual EA score distribution and (for panel A) report average values of own and parents' education, separately for males and females, for the genotyped individuals belonging to a household in the sample. Column 5 reports the difference in average values between the fourth and first quartiles, while col. 6 displays the *p*-value associated with this difference. Panel B conducts a similar exercise for household wealth and income.

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

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

retired households may introduce selection bias if the EA score is associated with the timing of retirement.

In table 3, we assess selection in our analytical sample by examining the relationship between the EA score and demographic characteristics that should be uncorrelated with the score in the absence of sample selection. Specifically, we divide individuals into quartiles on the basis of their individual EA scores and report the fraction of males, average birth year, and average age for each quartile. Sex and birth year are measured cross sectionally, while we include all person-year observations when calculating statistics for age. In panel A, we examine these patterns in our analytical sample, which includes all retired households with members aged 65–75. We indeed find selection on all three demographic variables. High-educational-attainment individuals (fourth quartile) are 4.5% more likely to be male than low-educational-attainment individuals (first quartile). Because the SNPs used to construct the EA score are not found on sex chromosomes, the slightly higher representation of men in the fourth quartile

TABLE 3
EA SCORE AND SELECTION

Individual EA Score and Individual Variables	Q1 (1)	Q2 (2)	Q3 (3)	Q4 (4)	Q4 – Q1 (5)	Q4 – Q1 <i>p</i> -Value (6)
A. Retired households, ages 65–75 (main sample):						
Male	.38	.41	.41	.43	.045	.057
Birth year	1935.19	1934.65	1934.28	1934.00	–1.19	<.01
Age	69.96	70.05	70.09	70.29	.33	<.01
B. Retired households, ages 55–85:						
Male	.38	.39	.41	.42	.04	.049
Birth year	1934.89	1934.65	1933.30	1932.90	–1.98	<.01
Age	70.89	71.13	71.85	72.31	1.42	<.01
C. All households, ages 50–75:						
Male	.42	.43	.42	.44	.026	.13
Birth year	1939.98	1939.64	1939.17	1939.31	–.68	.02
Age	63.64	63.40	63.62	63.43	–.22	.05
D. All households, ages ≤85:						
Male	.40	.41	.41	.43	.02	.12
Birth year	1938.56	1938.22	1937.28	1937.39	–1.17	<.01
Age	65.65	65.83	66.35	66.36	.72	<.01

NOTE.—This table assesses the relationship between the EA score and gender, birth year, and age in alternate samples. Columns 1–4 separate individuals into quartiles (Q1–Q4) of the individual EA score distribution and report average values of demographic variables for each quartile. Column 5 reports the difference in average values of each variable between the fourth and first educational attainment quartiles, while col. 6 reports the *p*-values associated with these differences. In panel A, we consider our baseline sample of retired households with members aged 65–75. In panel B, we report statistics for a larger sample that includes retired households with members aged 55–85. In panel C, we consider a sample that includes all households (retired and nonretired) with members aged 50–75. Panel D includes all households with members aged no more than 85.

of the EA score must result from selection. We also note that individuals with higher EA scores are more likely to belong to older birth cohorts and are more likely to be observed at old ages. These age and cohort differences are likely to arise if individuals with higher EA scores live longer on average (which we explore in sec. V) and are therefore more likely to survive to be genotyped and less likely to die and exit the panel. While these differences are statistically significant, they appear to be modest in size. The average difference in birth year between the fourth and the first quartiles is 1.2 years, while the average difference in age is 0.33 years.

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

IV. The EA Score and Wealth

A. *Main Association*

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

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

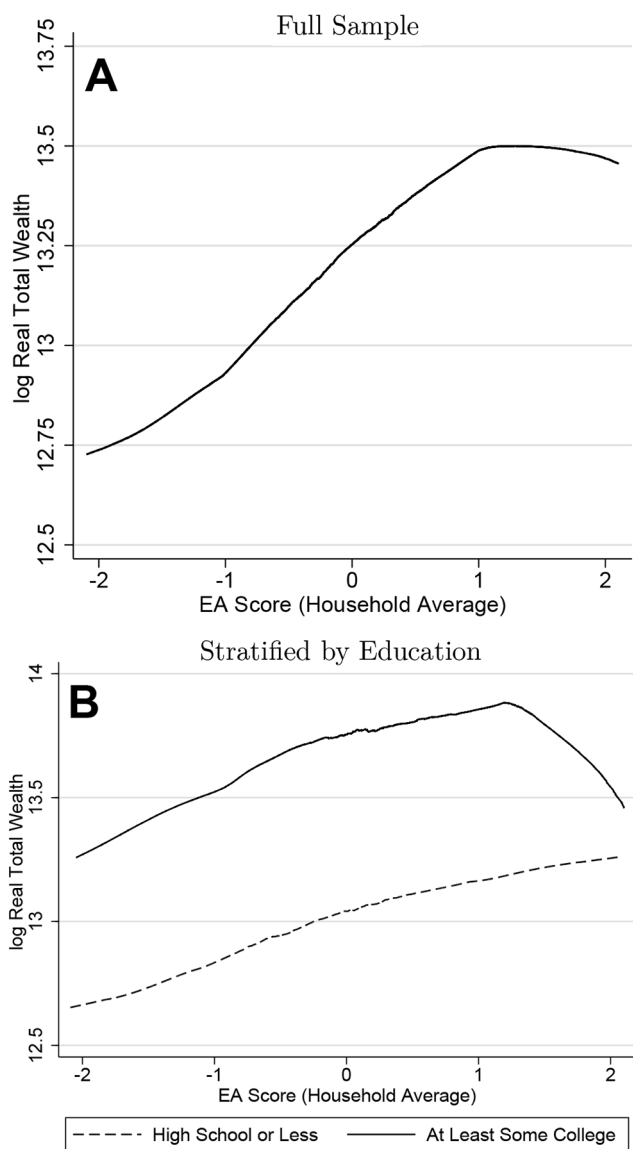


FIG. 2.—*A*, Average household EA score versus log household wealth, using data for all household-year observations in the analytic sample. *B*, Same relationship for two subsamples of households, the first with a maximum education level of a high school degree or less and the second with at least one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

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

Figure 2 and table 2 offer compelling evidence that the EA score and wealth are positively associated. We examine this relationship more formally in table 4, which reports results from regressing log household wealth on the EA score for specifications with various sets of controls.

TABLE 4
AVERAGE HOUSEHOLD EA SCORE AND HOUSEHOLD WEALTH

	DEPENDENT VARIABLE: LOG WEALTH						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
EA score	.246*** (.022)	.221*** (.020)	.218*** (.020)	.085*** (.021)	.070*** (.023)	.179*** (.020)	.047** (.022)
Male education				.061*** (.009)			
Female education				.122*** (.010)			
Log income						.316*** (.039)	.263*** (.038)
Observations	5,621	5,621	5,621	5,621	5,621	5,308	5,308
R ²	.054	.251	.279	.368	.435	.349	.479
Standard controls		X	X	X	X	X	X
Principal components			X	X	X	X	X
Years of education				X			
Full education controls					X		X

NOTE.—This table presents estimates from regressions of log household wealth on average household EA score and varying sets of controls. Column 1 includes no controls. Column 2 includes controls for age, birth cohort, sex of respondent, and calendar year, as described in sec. IV.B. Column 3 adds controls for principal components of the genetic data for genotyped household members. Column 4 adds years of education separately for both female and male household members. Column 5 replaces the two schooling variables with our full set of education controls (dummies for years of education, degree dummies, and interactions as described in sec. IV.B). Column 6 includes the log of total household income but excludes any controls for education. Column 7 includes our full set of controls, including the detailed education variables and the log of total household income. Standard errors are clustered at the family level.

** $p < .05$.

*** $p < .01$.

Standard errors are clustered at the family level.²¹ Column 1 shows the unconditional relationship between the EA score and the log of household wealth with no additional covariates. A 1 standard deviation increase in the EA score is associated with 24.6% greater wealth, and this result is highly statistically significant. In column 2, we add basic controls for age (separately for males and females in each household), birth year (separately for males and females), sex of the FR, calendar time, and family structure.²² Throughout the paper, these constitute our “standard controls.” The inclusion of standard controls has only a modest effect on the coefficient on the EA score, which remains large and highly significant. In column 3, we include the first 10 principal components of the genetic data and allow coefficients to vary for male and female household members.²³ These variables are intended to approximate family fixed effects as explained in section II (Benjamin et al. 2012). The principal components reduce the EA score coefficient from 0.221 to 0.218, and it remains statistically significant.

In column 4 of table 4, we add controls for years of schooling for each member of the household. Including years of schooling significantly reduces the size of the gene-wealth gradient, decreasing the coefficient to 0.085. This is unsurprising; the EA score was developed on the basis of years of schooling, and education undoubtedly affects income and wealth accumulation over the life cycle. It is important to note, however, that the coefficient remains statistically and economically significant even after controlling for years of schooling. A coefficient of 0.085 suggests that a 1 standard deviation increase in the genetic score is associated with approximately 8.5% greater wealth during retirement. In column 5, we include more flexible measures of education. Instead of the simple count of years of schooling for each member, we include the following: a complete set of dummy variables for each year of schooling for the male household

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

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

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

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

In column 6, we include the standard controls and principal components and add controls for labor income. In particular, we include the total of lifetime earnings for the household from the SSA data described in section III. Controlling for income reduces the coefficient on the EA score from 0.218 to 0.179, which remains statistically significant. In column 7, we add the full set of education variables along with income and other controls. The results are consistent with columns 5 and 6. The coefficient on the EA score is 0.047 ($p = .03$), suggesting that a 1 standard deviation increase in the EA score is associated with 4.7% greater wealth.

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

Given results linking higher-quality teachers to higher adult earnings (Chetty, Friedman, and Rockoff 2014), observed lifetime earnings may contain information about the quality of schools that an individual attended. Since controlling for lifetime earnings attenuates the relationship between the EA score and wealth, higher values of the polygenic score may be associated with access to better-quality schooling. However, controlling for lifetime income causes the coefficient on the polygenic score to shrink by at most one-third, leaving a substantial unexplained gradient. Nonetheless, measurement error in income is still a concern. It may be that

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

complete measures of income that do not suffer from top coding or reporting biases fully account for the gene-wealth gradient once education (even improperly measured) is included. While we assess the robustness of our results to various income specifications below, the reader should interpret our results with these potential measurement issues in mind.

B. Robustness

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

TABLE 5
AVERAGE HOUSEHOLD EA SCORE AND HOUSEHOLD WEALTH: ROBUSTNESS

	DEPENDENT VARIABLE: LOG WEALTH					
	(1)	(2)	(3)	(4)	(5)	(6)
FR EA score	.083*** (.025)	.070*** (.025)				
NFR EA score	.023 (.023)	.019 (.022)				
Average EA score			.079*** (.018)	.057*** (.018)	.071*** (.025)	.044* (.023)
Log income (SSA)		.211*** (.056)		.284*** (.029)		.197*** (.038)
Log income (HRS)						.221*** (.030)
Observations	1,927	1,870	18,925	17,563	3,993	3,833
R ²	.476	.507	.358	.387	.454	.512
Include nonretired households			X	X		
Standard controls	X	X	X	X	X	X
Principal components	X	X	X	X	X	X
Full education controls	X	X	X	X	X	X

NOTE.—This table provides estimates from three different robustness checks. In each case, log household wealth is the dependent variable and we show only results analogous to estimates in cols. 5 (with the full set of education controls) and 7 (full set of education controls and log income) of table 4. Columns 1 and 2 provide estimates from models where we condition on two EA scores per household, that of the FR and the NFR. Columns 3 and 4 provide estimates from models where we have increased the sample to include nonretired households. Columns 5 and 6 provide estimates of models that include two measures of income: the SSA lifetime income measure used in our main analyses along with the HRS measure of contemporaneous household income. Standard errors are clustered at the family level.

* $p < .1$.

*** $p < .01$.

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

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

In columns 3 and 4 of table 5, we relax the retirement requirement and include both retired and nonretired households. For nonretired households with defined-benefit pensions, economic resources are understated since we do not include expectations of future defined-benefit income. Compared with individuals in our main analytic sample, this sample includes individuals who are younger and more highly educated (by at least one-third of a year of schooling for both men and women) and who exhibit higher lifetime income (\$2.4 million vs. \$2.3 million for our baseline sample). The coefficients on the EA score in columns 3 and 4 are 0.079 and 0.057 (similar to our main results in table 4) and remain highly statistically significant. This suggests that our restriction to retired households

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

is not an important factor driving the relationship between the EA score and wealth. Nonetheless, we maintain the retirement restriction for our main sample to ensure completeness of the wealth data and to facilitate our analysis of the gene-wealth gradient within defined-benefit pension participation in section V.

Finally, in columns 5 and 6, we consider the log of the household's average self-reported labor income in the HRS as an additional control.²⁶ For this specification, we necessarily restrict the sample to households that are ever observed in the HRS with at least one working member, since this is required to obtain an in-sample measure of total income. The self-reported income data in the HRS are not subject to top coding like the SSA data. However, because the HRS is a sample of elderly Americans, this necessarily means that HRS labor income is observed toward the end of the life cycle or not at all. These differences are meaningful. Average annual household income in our sample based on HRS data is \$57,769, and the correlation coefficient between the log of this HRS average and the log of total income using SSA data is 0.32. Column 5 presents the coefficient on the EA score once we restrict the sample to households with nonmissing HRS income. The results in column 6 indicate that both the SSA and the HRS income variables independently predict wealth. Nevertheless, the estimated coefficient on the EA score is 0.044 ($p = .058$) when both income measures are included—similar to the baseline estimates in column 7 of table 4.

In appendix C, we provide numerous robustness tests for the main association between the EA score and wealth documented in table 4. Additional summary statistics, including those relevant for this section and later analyses, are included in appendix A.2. In separate analyses, we test the importance of sample selection by using HRS sampling weights, using only one household-year per sample, and restricting analyses to only “coupled” households—that is, those where two members are observed for at least one household-year observation. We also examine robustness to alternate sample definitions with different age restrictions, as well as those that include nonretirees. Additional specifications control for more complicated functions of household income, including the number of years with top-coded income, and use alternate definitions of household wealth that exclude retirement and housing wealth. We also examine robustness to the use of different versions of the EA score and to the inclusion of more extensive controls, including cognitive ability, number of children, the death of a household member, and years since retirement. Generally, results in table 4 are robust to these exercises.

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

C. *Transfers and Parental Education*

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

In table 6, we examine the extent to which the transfer of resources from parents to children—either indirectly through more advantageous environments as proxied by parental education or directly through monetary bequests—can explain the gene-wealth gradient.²⁷ Roughly 40% of households report receiving an inheritance, and among those who do, the average amount is approximately \$160,617. Average fathers' and mothers' education for the household are 9.47 and 9.95 years, respectively.

In column 1 of table 6, we provide a baseline specification that repeats column 5 of table 4 and includes the standard controls, principal components, and full education controls. In column 2, we include an indicator for ever receiving an inheritance in the HRS data and the log of total inheritances received by all members of the household while in the HRS. The log inheritance variable is set to zero for households that do not receive an inheritance. As expected, inheritances are highly correlated with household wealth. However, the inclusion of inheritances changes the coefficient on the EA score only marginally, from 0.070 to 0.064. Next, we include years of schooling for each parent of each member of the household, along with a set of dummy variables indicating missing values for these variables. The education of the father of the female member of

²⁷ In app. A, we provide additional summary statistics on these variables. We also show that after controlling for respondent education, the EA score is unrelated to the likelihood of receiving an inheritance or the size of the inheritance conditional on receiving one. Unsurprisingly, parental education is correlated with higher EA scores even after we control for respondents' education.

TABLE 6
INHERITANCES AND PARENTAL EDUCATION

	DEPENDENT VARIABLE: LOG WEALTH			
	(1)	(2)	(3)	(4)
EA score	.070*** (.023)	.064*** (.022)	.062*** (.023)	.058** (.023)
Any inheritance		−1.042*** (.172)		−.990*** (.171)
Log total inheritance		.121*** (.016)		.116*** (.016)
Father education (male)			.009 (.007)	.007 (.007)
Father education (female)			.021*** (.007)	.019*** (.007)
Mother education (male)			.014* (.007)	.010 (.007)
Mother education (female)			−.009 (.007)	−.012 (.007)
Observations	5,621	5,621	5,621	5,621
R ²	.435	.456	.442	.461
Standard controls	X	X	X	X
Principal components	X	X	X	X
Years of education	X	X	X	X
Full education controls	X	X	X	X

NOTE.—This table presents estimates from regressions of log household wealth on average household EA score and varying sets of controls. Column 1 includes the full set of controls from col. 5 of table 4. Column 2 includes an indicator for ever receiving an inheritance in the HRS, as well as the log of received inheritances (set to zero for those without an inheritance). Column 3 includes controls for parents' years of education, along with separate dummy variables indicating missing values for each of the four parental education variables. Column 4 includes both the inheritance variables and the parental education variables. Standard errors are clustered at the family level.

* $p < .1$.

** $p < .05$.

*** $p < .01$.

the household appears to be related to wealth, but the inclusion of parental education as a control once again reduces the coefficient on the EA score only slightly. In column 4, we include both parental education controls and the log of the sum of lifetime inheritances. The inclusion of the full set of proxies for parental investments reduces the coefficient on the EA score to 0.058, implying that a 1 standard deviation increase in the EA score increases total wealth by 5.8% and remains statistically significant at the 5% level.

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

mechanisms not examined in this section. We address potential alternative mechanisms in the following section.

V. Additional Mechanisms

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

A. Mortality

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

The 1-year mortality rate in our sample (excluding years before genotyping) is 0.04. The average subjective probability of living to 75 years old for individuals in our analytic sample is approximately 67%. We begin our analyses by directly estimating the empirical relationship between the individual's EA score and mortality. Since here we are studying individual

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

mortality outcomes, we use the individual’s own personal EA score as opposed to the household average score. We construct an indicator variable equal to one if the individual dies in the next year and estimate a linear probability model of the likelihood of dying in a particular year as a function of the individual’s EA score, the principal components, and dummy variables for age, birth year, years of schooling, and degree. We restrict this regression to person-years in which an individual was between the ages of 50 and 90, and we drop years before an individual was genotyped. Table 7 provides the results of this regression. In column 1, we include both females and males in the sample and find that a 1 standard deviation increase in the individual’s EA score is associated with a 0.3 percentage point decline in the 1-year mortality rate. Columns 2 and 3 consider females and males separately. The estimated association for females implies a 0.5 percentage point decline in the mortality rate for every 1 standard deviation increase in the EA score. We find no relationship for males.

We also consider beliefs about mortality. In principle, objective mortality should affect behavior only if individuals expect to live longer. In this sense, beliefs about mortality are perhaps the more relevant mechanism linking genetic endowments to wealth. The HRS repeatedly asks individuals to provide their subjective beliefs for the probability that they will live to the age of 75. In column 4, we regress this subjective belief on the individual EA score, our standard controls, and the full set of education controls in a sample of individuals aged 50–65. We do not find a significant

TABLE 7
MORTALITY

	DEPENDENT VARIABLE: OBSERVED MORTALITY			DEPENDENT VARIABLE: EXPECTED MORTALITY, Pr(Live to 75)		
	All Individuals (1)	Females (2)	Males (3)	All Individuals (4)	Females (5)	Males (6)
EA score	−.003* (.001)	−.005*** (.002)	.000 (.002)	.418 (.286)	.659* (.370)	−.316 (.482)
Observations	26,733	14,780	7,419	29,119	17,433	11,686
R ²	.035	.032	.029	.118	.130	.150

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

* $p < .1$.
*** $p < .01$.

association between the EA score and the level of this subjective probability. We also estimate this regression for females and males separately in columns 5 and 6 and find that for females a 1 standard deviation rise in the individual's EA score predicts a 0.66 percentage point rise in reported beliefs about living to age 75. For males, the relationship is negative and statistically insignificant. In total, we find a nontrivial relationship between the EA score and mortality rates but no association with expected mortality. This may offer some evidence that part of the gene-wealth gradient arises from the prospect of greater longevity.

B. Risk Aversion

We next examine whether the EA score is associated with differences in how households save. A well-established source of heterogeneity in household wealth is returns to risky endeavors, such as participation in risky asset markets or business ownership. One mechanism that may therefore relate the EA score to wealth is aversion to risk. To examine the relationship between risk aversion and the EA score, we use questions in the HRS designed to elicit measures of risk tolerance on the basis of hypothetical income and wealth gambles. Generally, these questions pose hypothetical scenarios in which the respondent faces a choice between a guaranteed endowment of wealth or stream of income or a 50–50 gamble that will result in a permanent increase or decrease in that endowment or income. Specifically, respondents are asked to choose between two jobs: “The first would guarantee your current total family income for life. The second is possibly better paying, but the income is also less certain. There is a 50–50 chance the second job would double your total lifetime income and a 50–50 chance that it would cut it by X .” The series replaces X with a set of possible income losses: 10%, 20%, one-third, one-half, or 75%. Additionally, respondents are asked one of two hypothetical wealth gambles with a similar structure. One is based on an inherited business worth \$1 million today or that may be sold in 1 month with a 50–50 chance of being worth \$2 million or X . The other is based on an immediate inheritance worth \$1 million with the potential to participate in a risky business venture that has a 50–50 chance of doubling in value or falling in value by X . In each case, X varies by the same proportions as the hypothetical income gamble.

On the basis of the responses to these hypothetical gambles, each respondent can be grouped by the smallest downside for which they still reject the gamble. We create a dummy variable for each gamble that takes a value of one if an individual always responds with a preference for the guaranteed wealth or income. A value equal to one for this variable indicates the highest degree of risk aversion permitted with this set of questions. Thirty-nine percent of respondents comprise the most risk-averse households, who would not take a 50–50 gamble that would double their

income or cut it by 10%. Alternatively, only 5% of respondents would take a 50–50 gamble where the downside is a 75% reduction in income.

In column 1 of table 8, the dependent variable is our binary indicator for the highest degree of risk aversion based on the labor income gamble. We find a negative association between the average household EA score and risk aversion—a 1 standard deviation increase in the score is associated with a reduction in the probability of the most risk-averse response by 2.2 percentage points. In columns 2 and 3, we use indicators for greatest risk aversion based on the inheritance and business risk questions as the dependent variables. We find no statistically significant relationship between the EA score and risk aversion for the inheritance question, but we do find that the probability of a respondent giving the most risk-averse response for the business risk question is 2.7 percentage points lower for a 1 standard deviation increase in the EA score, which is significant at the .05 level.

In columns 4–6, we allow the outcome variable to be an ordered categorical variable indicating the riskiest gamble that a respondent accepts. This variable can take one of six values, with higher values corresponding to higher degrees of risk aversion. We estimate an ordered probit model in these specifications and report coefficients for the latent index. Column 4 shows that the EA score is associated with a significant decrease in the latent index for risk aversion for income. Columns 5 and 6 repeat

TABLE 8
RISK AVERSION

	DEPENDENT VARIABLE: RISK AVERSION INDICATOR			DEPENDENT VARIABLE: RISK AVERSION CATEGORY		
	Income (1)	Inheritance (2)	Business (3)	Income (4)	Inheritance (5)	Business (6)
EA score	−.022*** (.007)	−.004 (.012)	−.027** (.011)	−.045*** (.015)	.017 (.029)	−.057** (.027)
Observations	10,512	2,951	2,912	10,512	2,951	2,912
R ²	.105	.210	.246			
Mean outcome	.39	.51	.47			
Standard controls	X	X	X	X	X	X
Principal components	X	X	X	X	X	X
Full education controls	X	X	X	X	X	X

NOTE.—This table presents estimates from regressions of measures of individual risk tolerance on the EA score and various controls. Risk tolerance is elicited from questions based on risky gambles over labor income, inheritance wealth, and business wealth. In cols. 1–3, the dependent variable is an indicator that takes a value of one for individuals who never choose the risky option over a guaranteed outcome. In cols. 4–6, we report estimates from ordered probit models where the outcome is a categorical variable that takes one of six values depending on the riskiest gamble that an individual accepts, with higher values indicating greater risk aversion. Standard errors are clustered at the family level.

** $p < .05$.

*** $p < .01$.

the ordered probit estimation for the inheritance and business wealth gambles, respectively. Again, we find no statistically significant relationship between the EA score and risk aversion based on the hypothetical inheritance wealth gambles, but we do find a significant relationship with risk aversion for the business wealth gamble.

C. Stocks, Housing, and Business Ownership

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

Panel A of table 9 regresses indicator variables for stock market participation, business ownership, and home ownership on the average household EA score and our full set of standard controls, including education variables. Columns 1–3 also include the log of total lifetime household income from the SSA data as an additional control. In column 1, we find no statistically significant relationship between home ownership and the EA score, but we do find a significant relationship between home ownership and lifetime earnings. In column 2, we find no relationship between business ownership and the EA score or between business ownership and lifetime labor income. Column 3, however, shows a strong positive association between the EA score and stock market participation. A 1 standard deviation increase in the EA score is associated with a 5.2 percentage point increase in the probability of owning stocks, and this coefficient is statistically significant at the 1% level. Compared to an average rate of stock ownership of 46%, the coefficient suggests that this predicted increase in participation is also economically meaningful.

Of course, stock market participation is likely affected by accumulated wealth, which has already been shown to strongly correlate with the EA score. This suggests that the relationships between the EA score and stock market participation may operate purely through wealth. This possibility is addressed in columns 4–6, which repeat the specifications in columns 1–3 but also include the log of financial wealth from the previous wave. Consistent with the existing literature, we find that the coefficient on lagged wealth is large and statistically significant for all three asset types. We continue to find no evidence of a relationship between the EA score and home or business ownership after controlling for lagged wealth. However, the relationship between the EA score and stock ownership remains significant and economically meaningful after controlling for lagged wealth. A 1 standard deviation increase in the EA score is associated with a

4 percentage point higher likelihood of owning stocks, with statistical significance at the 1% level. Because stocks have traditionally offered substantially higher returns than other liquid securities, such as money-market funds or bonds, this may be an important factor for explaining the gene-wealth gradient and may also suggest that these genetic endowments provide a microfoundation for the persistent differences in returns to wealth.

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

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

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

D. Extreme Beliefs and Planning Horizons

An important element of financial decision-making is an assessment of the risks and uncertainties associated with the macroeconomy and the

TABLE 9
AVERAGE HOUSEHOLD EA SCORE AND PORTFOLIO DECISIONS

	Dependent Variable: Owns House (1)	Dependent Variable: Owns Business (2)	Dependent Variable: Owns Stocks (3)	Dependent Variable: Owns House (4)	Dependent Variable: Owns Business (5)	Dependent Variable: Owns Stocks (6)
A. EA Score and Ownership of Assets						
EA score	.003 (.008)	.005 (.006)	.052*** (.011)	-.008 (.008)	-.001 (.006)	.040*** (.011)
Log income	.033*** (.008)	-.004 (.006)	.062*** (.011)	.002 (.008)	-.021*** (.008)	.021 (.013)
Lagged log wealth				.122*** (.009)	.047*** (.007)	.151*** (.016)
Observations	6,460	6,460	5,450	4,649	4,649	4,196
R^2	.304	.160	.348	.399	.217	.435
Mean outcome	.84	.08	.46	.83	.08	.47
Standard controls	X	X	X	X	X	X
Principal components	X	X	X	X	X	X
Full education controls	X	X	X	X	X	X

	Dependent Variable: Log Wealth		
	B. EA Score and Log Household Wealth		
EA score	.049** (.023)	.046** (.021)	.016 (.021)
Owens stocks			.507*** (.029)
Has business		.594*** (.049)	.530*** (.044)
Owens home		.887*** (.054)	.741*** (.052)
Observations	4,912	4,912	4,912
R^2	.487	.504	.599
Standard controls	X	X	X
Principal components	X	X	X
Full education controls	X	X	X
Log income	X	X	X

NOTE.—Panel A presents estimates from regressions of indicators for ownership of different asset types on the EA score and various controls. Panel B presents estimates from regressions of log household wealth on the EA score, indicators for ownership of different asset types, and various controls. Standard errors are clustered at the family level.

** $p < .05$.

*** $p < .01$.

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

Recent literature examines the role of subjective expectations in economic decisions such as human capital investments (Wiswall and Zafar 2015) and stock market participation (Arrondel, Calvo Pardo, and Tas 2014). Another set of papers demonstrates links between subjective beliefs and investment behaviors that impact household wealth (Lillard and Willis 2001; Dominitz and Manski 2007; Hudomiet, Kézdi, and Willis 2011).²⁹ Lumsdaine and Potter van Loon (2018) study differences in how individuals report beliefs about stock market returns, arguing that their findings reflect heterogeneity in individuals' understanding of the laws of probability. In related work, Lusardi, Michaud, and Mitchell (2017) demonstrate that heterogeneity in returns to savings, which are plausibly determined by financial knowledge, can explain a substantial proportion of wealth inequality.

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

- Stock market goes up: “By next year at this time, what is the percent chance that mutual fund shares invested in blue chip stocks like those in the Dow Jones Industrial Average will be worth more than they are today?”
- Economic depression: “What do you think are the chances that the US economy will experience a major depression sometime during the next 10 years or so?”

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

- Double-digit inflation: “And how about the chances that the US economy will experience double-digit inflation sometime during the next 10 years or so?”

First, we construct one (of possibly many) measure of “objectively correct” responses to these questions. Our objective benchmark probability for the stock market going up in a single year is 71%, which is the probability that the S&P 500 increases in value in a given year for the period 1992–2015. There is no common definition of an economic depression, but clearly this refers to an unusually severe period of economic contraction. We use data from the Federal Reserve Bank of St. 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% , which is the 25th percentile of the distribution of growth rates for negative-growth years. On the basis of this metric, the unconditional probability of a severe contraction is 4.4% per year, which implies a 36% probability for such an event over a 10-year period. Finally, the Bureau of Labor Statistics reports 2 years with double-digit inflation (1980, 1981) over the period 1958–2015. This implies an approximate probability of 3.4% for double-digit inflation in any year or about a 29% chance for double-digit inflation over a 10-year period.³⁰

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

Columns 2–4 in panel B of table 10 examine binary outcomes indicating whether respondents answered with specific focal probabilities (0, 50,

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

TABLE 10
EXTREME BELIEFS AND PLANNING HORIZONS

	Dependent Variable: Deviation (1)	Dependent Variable: Probability = 0 (2)	Dependent Variable: Probability = .5 (3)	Dependent Variable: Probability = 1 (4)
A. EA Score and Beliefs				
Stock market goes up:				
EA score	-.567*** (.162)	-.006*** (.002)	-.003 (.003)	-.002 (.001)
Observations	35,842	35,842	35,842	35,842
R^2	.097	.062	.030	.048
Mean outcome	28.31	.05	.30	.04
Depression:				
EA score	-.550*** (.138)	-.005** (.002)	-.003 (.003)	-.008*** (.002)
Observations	35,912	35,912	35,912	35,912
R^2	.088	.047	.037	.072
Mean outcome	24.94	.07	.26	.06
Double-digit inflation:				
EA score	-1.054*** (.193)	-.004** (.002)	-.005 (.004)	-.011*** (.002)
Observations	22,604	22,604	22,604	22,604
R^2	.080	.057	.044	.072
Mean outcome	26.10	.06	.34	.07

	Dependent Variable: PH ≥ 1 Year	Dependent Variable: PH \geq Few Years	Dependent Variable: PH $\geq 5-10$ Years	Dependent Variable: PH > 10 Years
	B. EA Score and PHs			
EA score	.008*** (.003)	.011*** (.004)	.013*** (.004)	.004 (.003)
Observations	27,752	27,752	27,752	27,752
R^2	.072	.081	.077	.045
Mean outcome	.87	.75	.45	.11
Standard controls	X	X	X	X
Principal components	X	X	X	X
Full education controls	X	X	X	X

NOTE.—Panel A presents estimates from regressions of beliefs about probabilities of three macroeconomic events on the EA score and various controls. Separate estimates are given for three distinct macroeconomic events: an increase in the stock market over the next year, a major depression in the next 10 years, and double-digit inflation in the next 10 years. In col. 1, the dependent variable is the absolute value of the deviation of the respondent's belief from an "objective" probability (as described in sec. V.E). The outcome variables in cols. 2, 3, and 4 are indicators for providing subjective probabilities of 0, .5, and 1, respectively. Panel B presents estimates from regressions of indicator variables for the length of a respondent's financial planning horizon (PH) on the EA score and various controls. In col. 1, the dependent variable is an indicator for reporting a PH greater than or equal to 1 year. In cols. 2, 3, and 4, the dependent variables are indicators for horizons of "greater than or equal to a few years," "greater than or equal to 5–10 years," and "greater than 10 years," respectively. Standard errors are clustered at the family level.

** $p < .05$.

*** $p < .01$.

and 100, respectively). Using linear probability models, we relate these binary outcomes to the EA score. For all three events, we observe the same pattern of association: the EA score is negatively associated with providing a subjective probability indicating complete certainty (0 or 100) and is largely uncorrelated with providing a focal probability of 50%. The magnitudes of these associations are substantial. For example, findings on beliefs about a depression suggest that a 1 standard deviation increase in the EA score is associated with a 0.5 percentage point reduction in the probability of reporting a 0% probability that the economy will suffer a major depression in the next 10 years. For comparison, 7% of individuals report a 0% probability for this event. While we find no statistically significant association between the EA score and reporting a 100% probability that the stock market will increase, we do find a relationship between 100% beliefs about economic recessions and double-digit inflation.

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

In panel B of table 10, we test whether the EA score predicts planning horizon responses. The dependent variable in column 1 is a dummy variable equal to one if the planning horizon is greater than a few months. The estimated coefficient is statistically significant and suggests that a 1 standard deviation in the EA score is associated with a 0.8 percentage point increase in the probability of reporting a planning horizon longer than a few months. Columns 2–4 repeat this exercise but with dummies equal to one for increasingly longer horizons. The dummy dependent variable in column 2 is equal to one if the reported horizon is “a few years,” in column 3 if “5–10 years,” and in column 4 if “longer than 10 years.” In all

but column 4, the coefficient on the EA score is positive and significant at the 1% level. This suggests that the EA score is predictive of longer planning horizons for all but the longest horizon.

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

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

E. Pensions

One consequence of the apparent relationship between genetic endowments and financial decisions is that individuals with low EA scores may benefit from outsourcing certain economic choices, such as saving and investment decisions. Defined-benefit pensions, which may be provided

by one's employer, offer one form of outsourcing by providing an employee a guaranteed stream of income in retirement without requiring the individual to choose the contribution rate or underlying investment allocations. Defined-benefit plans effectively reduce the impact of the household's financial decisions on accumulated wealth by ensuring a minimal level of resources at retirement. We investigate whether the reduced autonomy associated with defined-benefit pensions alters the relationship between genetic ability and wealth.³¹

Over half of households (57%) have a defined-benefit pension, with an average present discounted value of \$234,021. One primary concern is that pension participation is not randomly assigned. As a first step, we regress an indicator for defined-benefit pension participation on the average household EA score. Column 1 of table 11 shows that after including our standard set of controls, there is no economically or statistically significant relationship between the EA score and defined-benefit pension participation. Column 2 shows that conditional on participation in a defined-benefit pension plan, defined-benefit pension wealth (the present value of pension income) is also unrelated to the EA score. In general, selection into careers based on defined-benefit pension benefits appears to be uncorrelated with the EA score after controlling for education.

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

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

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

TABLE 11
PENSIONS AND HOUSEHOLD WEALTH

	Dependent Variable: Has Pension (1)	Dependent Variable: Pension Wealth (2)	Dependent Variable: Log Wealth (3)	Dependent Variable: Log Wealth (4)
EA score	.003 (.011)	.030 (.035)	.069*** (.022)	.125*** (.035)
DB pension			.385*** (.035)	.181*** (.051)
EA score × DB pension				−.096*** (.036)
Observations	5,621	3,226	5,621	5,621
R ²	.215	.400	.460	.474
Mean outcome	.57	\$234,021		
Standard controls	X	X	X	X
Principal components	X	X	X	X
Full education controls	X	X	X	X

NOTE.—Columns 1 and 2 present estimates from regressions of defined-benefit (DB) pension participation and log pension wealth (conditional on participation) on the EA score and various controls. Columns 3 and 4 present estimates from regressions of log household wealth on the EA score, DB pension participation, an interaction between the EA score and pension participation, and various controls. Standard errors are clustered at the family level.
*** $p < .01$.

is in part determined by a household’s difficulty in making wise financial choices.

VI. Conclusions

We study the genetic endowments linked to educational attainment, summarized as a linear index called a polygenic score (EA score). Using data from the HRS, we demonstrate that the average EA score in a household strongly and robustly predicts wealth at retirement. The estimated gene-wealth gradient is not fully explained by flexibly controlling for education and income or by parental transfers (bequests) and parents’ education, which may proxy for parental investments. We find that the EA score is related to risk preferences and mortality and strongly predicts stock ownership. Stock market participation appears to substantially mediate the gene-wealth association. Lower EA scores are associated with less accurate beliefs about macroeconomic probabilities, as well as shorter planning horizons. Finally, the EA score is much more strongly related to wealth within a subsample of individuals who do not receive defined-benefit pension benefits and who presumably have greater autonomy over their financial decisions.

The associations we report not only help us to explain the gene-wealth gradient but may also suggest why these particular genetic markers are associated with education. In particular, the finding that the EA score is related to probabilistic thinking, planning horizons, and decision-making

under uncertainty may be useful for understanding the sources of heterogeneity in human capital accumulation. However, we offer important caveats for such an interpretation of these findings. First, measurement error in income, education, and parental transfers may lead us to incorrectly ascribe part of the gene-wealth gradient to other factors that would be unrelated if such variables were correctly measured. Second, genetic measures are likely endogenous to family environment, so one must be careful before assigning a causal interpretation to the gene-outcome gradients that we observe. Third, the polygenic score does not fully explain the amount of education that twins studies have suggested is heritable. Future GWASs will likely estimate more precise genetic associations that could lead to stronger empirical relationships between a polygenic score and completed schooling and that could alter the empirical relationships documented here.

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

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

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

References

- Abdulkadiroğlu, Atila, Joshua Angrist, and Parag Pathak. 2014. "The Elite Illusion: Achievement Effects at Boston and New York Exam Schools." *Econometrica* 82 (1): 137–96.
- Angrist, Joshua D., Sarah R. Cohodes, Susan M. Dynarski, Parag A. Pathak, and Christopher R. Walters. 2016. "Stand and Deliver: Effects of Boston's Charter High Schools on College Preparation, Entry, and Choice." *J. Labor Econ.* 34 (2): 275–318.
- Arrondel, Luc, Hector F. Calvo Pardo, and Derya Tas. 2014. "Subjective Return Expectations, Information and Stock Market Participation: Evidence from France." Working paper, Univ. Southampton.
- Bach, Stefan, Andreas Thiemann, and Aline Zucco. 2015. "The Top Tail of the Wealth Distribution in Germany, France, Spain, and Greece." Working Paper no. 1502, German Inst. Econ. Res. Berlin.
- Beauchamp, Jonathan P., David Cesarini, Magnus Johannesson, et al. 2011. "Molecular Genetics and Economics." *J. Econ. Perspectives* 25 (4): 57–82.
- Behrman, Jere R., and Nancy Birdsall. 1983. "The Quality of Schooling: Quantity Alone Is Misleading." *A.E.R.* 73 (5): 928–46.
- Belsky, Daniel W., Terrie E. Moffitt, David L. Corcoran, et al. 2016. "The Genetics of Success: How Single-Nucleotide Polymorphisms Associated with Educational Attainment Relate to Life-Course Development." *Psychological Sci.* 27:957–72.
- Benhabib, Jess, and Alberto Bisin. 2016. "Skewed Wealth Distributions: Theory and Empirics." Working Paper no. 21924 (January), NBER, Cambridge, MA.
- Benhabib, Jess, Alberto Bisin, and Mi Luo. 2015. "Wealth Distribution and Social Mobility in the US: A Quantitative Approach." Working Paper no. 21721 (November), NBER, Cambridge, MA.
- Benhabib, Jess, Alberto Bisin, and Shenghao Zhu. 2011. "The Distribution of Wealth and Fiscal Policy in Economies with Finitely Lived Agents." *Econometrica* 79 (1): 123–57.
- Benham, Lee. 1974. "Benefits of Women's Education within Marriage." *J.P.E.* 82 (2, pt. 2): S57–S71.
- Benjamin, Daniel J., David Cesarini, Christopher F. Chabris, et al. 2012. "The Promises and Pitfalls of Genoeconomics." *Ann. Rev. Econ.* 4:627–62.
- Bierut, Laura Jean. 2010. "Convergence of Genetic Findings for Nicotine Dependence and Smoking Related Diseases with Chromosome 15q24-25." *Trends Pharmacological Sci.* 31 (1): 46–51.
- Black, Sandra E., Paul J. Devereux, and Kjell G. Salvanes. 2005. "Why the Apple Doesn't Fall Far: Understanding Intergenerational Transmission of Human Capital." *A.E.R.* 95 (1): 437–49.
- Branigan, Amelia R., Kenneth J. McCallum, and Jeremy Freese. 2013. "Variation in the Heritability of Educational Attainment: An International Meta-analysis." *Soc. Forces* 92 (1): 109–40.
- Bulik-Sullivan, Brendan, Hilary K. Finucane, Verner Anttila, et al. 2015. "An Atlas of Genetic Correlations across Human Diseases and Traits." *Nature Genetics* 47 (11): 1236–41.
- Calvet, Laurent E., John Y. Campbell, and Paolo Sodini. 2007. "Down or Out: Assessing the Welfare Costs of Household Investment Mistakes." *J.P.E.* 115 (5): 707–47.
- Card, David, and Alan B. Krueger. 1996. "Labor Market Effects of School Quality: Theory and Evidence." Working Paper no. 5450 (February), NBER, Cambridge, MA.

- Cesarini, David, Christopher T. Dawes, Magnus Johannesson, Paul Lichtenstein, and Björn Wallace. 2009. "Genetic Variation in Preferences for Giving and Risk Taking." *Q.J.E.* 124 (2): 809–42.
- Cesarini, David, Magnus Johannesson, Paul Lichtenstein, Örjan Sandewall, and Björn Wallace. 2010. "Genetic Variation in Financial Decision-Making." *J. Finance* 65 (5): 1725–54.
- Charles, Kerwin Kofi, and Erik Hurst. 2003. "The Correlation of Wealth across Generations." *J.P.E.* 111 (6): 1155–82.
- Chetty, Raj, John N. Friedman, and Jonah E. Rockoff. 2014. "Measuring the Impacts of Teachers II: Teacher Value-Added and Student Outcomes in Adulthood." *A.E.R.* 104 (9): 2633–79.
- Cronqvist, Henrik, and Stephan Siegel. 2014. "The Genetics of Investment Biases." *J. Financial Econ.* 113:215–34.
- . 2015. "The Origins of Savings Behavior." *J.P.E.* 123 (1): 123–69.
- Delavande, Adeline, Michael Perry, and Robert Willis. 2006. "Probabilistic Thinking and Early Social Security Claiming." Working Paper no. 129, Michigan Retirement Res. Center, Univ. Michigan.
- Delavande, Adeline, Susann Rohwedder, and Robert J. Willis. 2008. "Preparation for Retirement, Financial Literacy and Cognitive Resources." Working Paper no. 190, Michigan Retirement Res. Center, Univ. Michigan.
- Deming, David J., Justine S. Hastings, Thomas J. Kane, and Douglas O. Staiger. 2014. "School Choice, School Quality, and Postsecondary Attainment." *A.E.R.* 104 (3): 991–1013.
- De Nardi, Mariacristina. 2004. "Wealth Inequality and Intergenerational Links." *Rev. Econ. Studies* 71 (3): 743–68.
- Dobbie, Will, and Roland G. Fryer Jr. 2011. "Are High-Quality Schools Enough to Increase Achievement among the Poor? Evidence from the Harlem Children's Zone." *American Econ. J.: Appl. Econ.* 3 (3): 158–87.
- Dominitz, Jeff, and Charles F. Manski. 2007. "Expected Equity Returns and Portfolio Choice: Evidence from the Health and Retirement Study." *J. European Econ. Assoc.* 5 (2/3): 369–79.
- Fagereng, Andreas, Luigi Guiso, Davide Malacrino, and Luigi Pistaferri. 2016. "Heterogeneity and Persistence in Returns to Wealth." Working Paper no. 22822 (November), NBER, Cambridge, MA.
- Fagereng, Andreas, Magne Mogstad, and Marte Rønning. 2015. "Why Do Wealthy Parents Have Wealthy Children?" Working Paper no. 813, Statist. Norway, Oslo.
- Feuk, Lars, Andrew R. Carson, and Stephen W. Scherer. 2006. "Structural Variation in the Human Genome." *Nature Rev. Genetics* 7:85–97.
- Gabaix, Xavier, and David Laibson. 2017. "Myopia and Discounting." Working Paper no. 23254 (March), NBER, Cambridge, MA.
- Grinblatt, Mark, Seppo Ikäheimo, Matti Keloharju, and Samuli Knüpfer. 2015. "IQ and Mutual Fund Choice." *Management Sci.* 62 (4): 924–44.
- Grinblatt, Mark, Matti Keloharju, and Juhani Linnainmaa. 2011. "IQ and Stock Market Participation." *J. Finance* 66 (6): 2121–64.
- Hudomiet, Peter, Gábor Kézdi, and Robert J. Willis. 2011. "Stock Market Crash and Expectations of American Households." *J. Appl. Econometrics* 26 (3): 393–415.
- Hurd, Michael D. 2009. "Subjective Probabilities in Household Surveys." *Ann. Rev. Econ.* 1:543–62.
- Jackson, C. Kirabo, Rucker C. Johnson, and Claudia Persico. 2015. "The Effects of School Spending on Educational and Economic Outcomes: Evidence from School Finance Reforms." *Q.J.E.* 131 (1): 157–218.

- Jones, Charles I. 2015. "Pareto and Piketty: The Macroeconomics of Top Income and Wealth Inequality." *J. Econ. Perspectives* 29 (1): 29–46.
- Kahneman, Daniel, and Amos Tversky. 1972. "Subjective Probability: A Judgment of Representativeness." In *The Concept of Probability in Psychological Experiments*, edited by Carl-Axel S. Staël von Holstein, 25–48. Dordrecht: Reidel.
- Kézdi, Gábor, and Robert J. Willis. 2003. "Who Becomes a Stockholder? Expectations, Subjective Uncertainty, and Asset Allocation." Working paper, Univ. Michigan.
- . 2009. "Stock Market Expectations and Portfolio Choice of American Households." Working paper, Univ. Michigan.
- . 2013. "Expectations, Aging and Cognitive Decline." In *Discoveries in the Economics of Aging*, edited by David A. Wise, 305–37. Chicago: Univ. Chicago Press.
- Kong, Augustine, Gudmar Thorleifsson, Michael L. Frigge, et al. 2018. "The Nature of Nurture: Effects of Parental Genotypes." *Science* 359 (6374): 424–28.
- Lee, James J., Robbee Wedow, Aysu Okbay, et al. 2018. "Gene Discovery and Polygenic Prediction from a 1.1-Million-Person GWAS of Educational Attainment." *Nature Genetics* 50:1112–21.
- Lillard, Lee, and Robert J. Willis. 2001. "Cognition and Wealth: The Importance of Probabilistic Thinking." Working Paper no. 07, Michigan Retirement Res. Center, Univ. Michigan.
- Locke, Adam E., Bratati Kahali, Sonja I. Berndt, et al. 2015. "Genetic Studies of Body Mass Index Yield New Insights for Obesity Biology." *Nature* 518 (7538): 197–206.
- Lumsdaine, Robin L., and Rogier J. D. Potter van Loon. 2018. "Do Survey Probabilities Match Financial Market Beliefs?" *J. Behavioral Finance* 19 (2): 209–20.
- Lusardi, Annamaria, Pierre-Carl Michaud, and Olivia S. Mitchell. 2017. "Optimal Financial Knowledge and Wealth Inequality." *J.P.E.* 125 (2): 431–77.
- Marioni, Riccardo E., Stuart J. Ritchie, Peter K. Joshi, et al. 2016. "Genetic Variants Linked to Education Predict Longevity." *Proc. Nat. Acad. Sci. USA* 113 (47): 13366–71.
- Martin, Alicia R., Christopher R. Gignoux, Raymond K. Walters, et al. 2017. "Human Demographic History Impacts Genetic Risk Prediction across Diverse Populations." *American J. Human Genetics* 100 (4): 635–49.
- Okbay, Aysu, Jonathan P. Beauchamp, Mark Alan Fontana, et al. 2016. "Genome-Wide Association Study Identifies 74 Loci Associated with Educational Attainment." *Nature* 533 (7604): 539–42.
- Okbay, Aysu, Daniel Benjamin, and Peter Visscher. 2018. "SSGAC Educational Attainment: GWAS and MTAG Polygenic Scores (Ver. 1.0)." Soc. Sci. Genetic Assoc. Consortium.
- Olsen, Anya, and Russell Hudson. 2009. "Social Security Administration's Master Earnings File: Background Information." Soc. Security Bull. no. 69 (3), Soc. Security Admin., Woodlawn, MD. <https://www.ssa.gov/policy/docs/ssb/v69n3/v69n3p29.html>.
- Papageorge, Nicholas W., and Kevin Thom. 2019. "Genes, Education and Labor Outcomes: Evidence from the Health and Retirement Study." *J. European Econ. Assoc.*, forthcoming.
- Poterba, James M., and David A. Wise. 1998. "Individual Financial Decisions in Retirement Saving Plans and the Provision of Resources for Retirement." In *Privatizing Social Security*, edited by Martin Feldstein, 363–401. Chicago: Univ. Chicago Press.

- Price, Alkes L., Nick J. Patterson, Robert M. Plenge, Michael E. Weinblatt, Nancy A. Shadick, and David Reich. 2006. "Principal Components Analysis Corrects for Stratification in Genome-Wide Association Studies." *Nature Genetics* 38 (8): 904–9.
- Rietveld, Cornelius A., Sarah E. Medland, Jaime Derringer, et al. 2013. "GWAS of 126,559 Individuals Identifies Genetic Variants Associated with Educational Attainment." *Science* 340 (6139): 1467–71.
- Rohwedder, Susann, and Robert J. Willis. 2010. "Mental Retirement." *J. Econ. Perspectives* 24 (1): 119–38.
- Ruggles, Steven, Sarah Floor, Ronald Goeken, et al. 2018. *Integrated Public Use Microdata Series USA: Version 8.0*. Minneapolis: Univ. Minnesota. doi:10.18128/D010.V8.0.
- Sacerdote, Bruce. 2011. "Nature and Nurture Effects on Children's Outcomes: What Have We Learned from Studies of Twins and Adoptees?" In *Handbook of Social Economics*, vol. 1A, edited by Jess Benhabib, Alberto Bisin, and Matthew O. Jackson, 1–30. Amsterdam: Elsevier.
- Saez, Emmanuel, and Gabriel Zucman. 2014. "Wealth Inequality in the United States since 1913: Evidence from Capitalized Income Tax Data." Working Paper no. 20625 (October), NBER, Cambridge, MA.
- Savage, Leonard J. 1954. *The Foundations of Statistics*. New York: Wiley.
- Scholz, John Karl, and Ananth Seshadri. 2007. "Children and Household Wealth." Working paper, Univ. Michigan.
- Thorgeirsson, Thorgeir E., Daniel F. Gudbjartsson, Ida Surakka, et al. 2010. "Sequence Variants at *CHRNA3-CHRNA6* and *CYP2A6* Affect Smoking Behavior." *Nature Genetics* 42 (5): 448–53.
- Venti, Steven F., and David A. Wise. 1998. "The Cause of Wealth Dispersion at Retirement: Choice or Chance?" *A.E.R.* 88 (2): 185–91.
- Vilhjálmsdóttir, Bjarni J., Jian Yang, Hilary K. Finucane, et al. 2015. "Modeling Linkage Disequilibrium Increases Accuracy of Polygenic Risk Scores." *American J. Human Genetics* 87:576–92.
- Ware, Erin, Lauren Schmitz, Arianna Gard, and Jessica Faul. 2018. "HRS Polygenic Scores: Release 3, 2006–2012 Genetic Data." Health and Retirement Study Documentation Report, Survey Res. Center, Univ. Michigan.
- Wiswall, Matthew, and Basit Zafar. 2015. "Determinants of College Major Choice: Identification Using an Information Experiment." *Rev. Econ. Studies* 82 (2): 791–824.
- Yogo, Motohiro. 2016. "Portfolio Choice in Retirement: Health Risk and the Demand for Annuities, Housing, and Risky Assets." *J. Monetary Econ.* 80:17–34.
- Zuk, Or, Eliana Hechter, Shamil R. Sunyaev, and Eric S. Lander. 2012. "The Mystery of Missing Heritability: Genetic Interactions Create Phantom Heritability." *Proc. Nat. Acad. Sci. USA* 109 (4): 1193–98.