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MOLECULAR GENETICS, RISK AVERSION, RETURN PERCEPTIONS, AND STOCK MARKET PARTICIPATION

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ABSTRACT

We show that molecular variation in DNA related to cognition, personality, health, and body shape, predicts an individual's equity market participation and risk aversion. Moreover, the molecular genetic endowments predict individuals' return perceptions, most of which we find to be strikingly biased. The genetic endowments also strongly associate with many of the investor characteristics (e.g., trust, sociability, wealth) shown to explain heterogeneity in equity market participation. Our analysis helps elucidate why financial choices are heritable and how genetic endowments can help explain the links between financial choices, risk aversion, beliefs, and other variables known to explain stock market participation.

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MOLECULAR GENETICS, RISK AVERSION, RETURN PERCEPTIONS, AND STOCK MARKET PARTICIPATION

"*Oh there ain't no other way, Baby I was born this way*"

-Lady Gaga

I. INTRODUCTION

An often-cited puzzle in financial markets derives from the fact that individuals' investment choices vary from the predictions of traditional utility maximizing theory. This theory prescribes that investors should hold at least some portion of their wealth in equity markets (e.g., Merton, 1969, 1971) and in fact, for most investors, almost all savings should be invested in equity (e.g., Heaton and Lucas, 1997). Moreover, the extensive heterogeneity across these choices has been linked to biological attributes (e.g., neurochemical activity), personality (e.g., trust), demographics (e.g., education), and physical (e.g., health) characteristics (Harlow and Brown 1990; Guiso, Sapienza, and Zingales 2008; Cole, Paulson, and Shastry 2014; Rosen and Wu 2004). A separate vein of research demonstrates the important role of genetic influences by estimating through "twin studies" how much of the heterogeneity in financial decisions for the Swedish population is heritable (e.g., Barnea, Cronqvist, and Siegel 2010; Cesarini, et al. 2010). However, little work exists to unify these findings and their implications.

Recent advances in molecular genetics allow us to use DNA variation across individuals to provide novel insights into *how* and *why* an individual's genome influences their financial choices and how these influences are related to previous research.[1] Thus, because we can now identify specific DNA variations associated with many observable characteristics or traits, we provide unification and linkages between two disparate literatures explaining individuals' financial decisions: heterogeneity in investor characteristics and heritability. Using a large panel data set from the Health and Retirement Study that includes financial, psychosocial, demographic, and

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[1] These advances include low cost genotyping and the development of consortium-based large scale Genome Wide Association Studies (GWAS).

genetic data for 5,130 individuals across time, we examine the role of specific genetic endowments in financial decisions. We focus on eight genetic endowments related to cognition (Educational Attainment and General Cognition), personality (Neuroticism and Depressive Symptoms), health (Myocardial Infarctions and Coronary Artery Disease) and body type (Height and BMI) and examine how these endowments help shape observed heterogeneity in financial decisions.[2]

Because the genome is determined at conception, and our sample consists of individuals aged 50 to 80, genetic endowments are established long before observation of an individual's stock market participation. Thus, we begin by hypothesizing relationships between individuals' genetic endowments and their equity market participation and test whether these endowments can *predict* heterogeneity in equity market participation more than half a century later. Consistent with our hypotheses, individuals with higher genetic endowments associated with Educational Attainment, General Cognition, and Height are more likely to invest in equity markets (and in addition invest a larger fraction of their wealth in risky assets) while individuals with higher genetic scores associated with Neuroticism, Depressive Symptoms, Myocardial Infarction, Coronary Artery Disease, and BMI exhibit lower equity market participation. Moreover, the effect sizes are substantial—a one standard deviation higher genetic endowment for Neuroticism predicts a 3.7% lower probability of holding any equity.

The balance of our study focuses on understanding how and why these eight genetic endowments predict equity market participation, and on how the heritability literature links to the investor characteristics literature. We first examine whether the genetic endowments predict heterogeneity in risk aversion and return beliefs—the factors driving heterogeneity in equity exposure within the traditional utility maximizing framework. The evidence supports the hypothesis that the genetic endowments predict stock market participation, at least in part, because they predict heterogeneity in individuals' risk aversion and return beliefs. For example, a higher

[2] Because we examine both genotypes (information from the genome) and phenotypes (observed traits), we capitalize genotype variables to reduce confusion, e.g., "Height" refers to the genetic endowment associated with height, often measured by a polygenic score (PGS), while "height" refers to an individual's observed height.

genetic endowment for Neuroticism predicts both greater risk aversion and more bearish beliefs regarding equity returns.

However, we also establish that the genetic endowments' ability to explain equity market participation does not derive solely through their ability to predict risk aversion and return beliefs. After accounting for these two channels, we find that most of the eight genetic endowments continue to predict equity market participation choices on their own. For example, after controlling for risk aversion and beliefs, a person with a one standard deviation larger genetic endowment for Neuroticism is still 2.8% less likely to hold any equity (as compared to 3.7% before controlling for risk aversion and beliefs). We propose that the genetic endowments continue to predict stock market participation after accounting for heterogeneity in risk aversion and beliefs across individuals because these biological metrics measure heterogeneity in risk aversion or beliefs beyond what is captured by an individual's self-reported values, and because they predict heterogeneity in circumstances (unrelated to risk aversion or beliefs) that impact stock market participation. For example, the genetic endowment for Cognition could predict the individual's current financial position and consequently their participation costs.

We next focus on the role of genetic endowments in linking the existing heritability literature with the existing literature tying investor characteristics to stock market participation. Examining this linkage allows us to help explain individuals' stock market participation choice through not only showing how the heritability literature connects to the investor characteristic literature but also showing the channels through which these genetic endowments predict stock market participation. Specifically, we take 11 previously identified investor characteristics—wealth, income, education, cognition, trust, sociability, optimism, growing up poor, height, BMI, and health—that help explain heterogeneity in stock market participation and examine their links to the eight genetic endowments. These characteristics are nearly uniformly hypothesized to impact heterogeneity in equity market participation via influencing heterogeneity in risk aversion, beliefs, or factors outside of classical models (i.e., heterogeneity in circumstances). For instance, Malmendier and Nagel (2011) hypothesize that an individual's life experience (e.g., experiencing an economic event such as a depression) impacts an individual's risk aversion and return beliefs and, *as a result*, the individual's equity market participation.

After documenting that the 11 investor characteristics explain stock market participation in the directions expected from prior work, we examine the relation between the investor characteristics and heterogeneity in risk aversion and return beliefs to understand the channels linking these variables to equity market participation. Because previous work tends to focus on risk aversion (as data regarding heterogeneity in beliefs has been scarce), our tests provide evidence, often for the first time, that most of these 11 explanatory variables are meaningfully associated with heterogeneity in *both* risk aversion and beliefs.

In a first step toward linking the heritability literature (i.e., twin studies) with the investor characteristics literature, we test whether the genetic endowments predict the investor characteristics that, in turn, help explain heterogeneity in the economic outcomes (equity market participation, risk aversion, and beliefs). Some of the links are obvious and direct—variation in a genetic predisposition for Height should predict variation in height, and taller individuals have been found to be more likely to participate in equity markets (Addoum, Korniotis, and Kumar, 2017). Even in less direct cases, however, intuition and previous work suggests genetic endowments should play a significant role in driving heterogeneity in these characteristics, e.g., higher neuroticism is associated with lower trust (Evans and Revelle, 2008) and lower trust is associated with lower equity market participation (Guiso, Sapienza, and Zingales, 2008). Consistent with the explanation that the molecular genetic endowments associated with cognition, personality, health, and body shape help determine these characteristics, each of the 11 investor characteristic variables is meaningfully related to at least three of the eight genetic endowments and the average characteristic is meaningfully related to 5.7 of the eight genetic scores. Moreover, the results are intuitive and consistent with phenotypic evidence—for example, an individual's self-rated health assessment is positively predicted by the two genetic endowments associated with cognition, but negatively predicted by five of the genetic endowments associated with personality, health, and body shape.

We investigate the specific channels through which each of the eight genetic endowments predicts the economic outcomes with a straightforward approach—we perform a sensitivity analysis of whether the predictability of a genetic endowment is subsumed by the inclusion of an investor characteristic. For example, we find that the genetic endowment for Height no longer predicts stock market participation once accounting for an individual's realized height, suggesting that the genetic endowment for Height predicts stock market participation because it predicts actual height and taller individuals are more likely to hold equities. For five of the eight genetic endowments, however, none of the 11 characteristics fully subsumes the genetic endowments' predictive ability, reflecting an independent effect, which could result from the failure of the observed investor characteristics to completely capture the important respondent phenotypes resulting from the particular genetic endowment. For instance, the genetic endowment for Neuroticism continues to predict less stock market participation after accounting for sociability. These tests not only help explain the channels linking genetic endowments to economic outcomes, but they also provide a direct linkage between the investor characteristics literature and the heritability literature. The fact that some portion of the ability of these eight genetic endowments to predict economic outcomes remains unexplained suggests additional, as yet unidentified, phenotypes or combinations of phenotypes link individuals' genetic endowments to their stock market participation, risk aversion, and return beliefs.

Our final set of tests estimate the relative magnitude of these eight genetic endowments in linking stock market participation to risk aversion and beliefs as well as the 11 investor characteristics we examine. It is important to understand how these tests differ from twin studies as each approach (twin studies and molecular genetics) has advantages and limitations. The goal of a twin study is to estimate phenotypic "heritability" (i.e., the percentage of the phenotype that is due to nature versus nurture). For example, twin study estimates suggest that unknown genetic endowments account for 20% of variation in risk preferences in Sweden (Cesarini, et al., 2009). However, twin studies cannot estimate the "genetic portion" of a subject's phenotype or provide evidence regarding why a phenotype is heritable. In contrast, molecular genetics is (arguably) poorly suited to estimate phenotypic heritability (due to the "missing heritability" issue discussed in the next section). Yet, because molecular genetic endowments are established for each individual in our sample, we can estimate links between phenotypes and specific genetic endowments. As a result, molecular genetics allows one to examine both how, and how much of, the *relation* between phenotypes may be attributed to specific genetic endowments. Thus, for example, we can establish the role of these eight genetic endowments in linking risk aversion to stock market participation. In short, molecular genetics provide a connection between specific genetic underpinnings and financial behavior, in contrast with the latent variable approaches available in twin studies.

Consistent with financial economic theory, we show that equity market participation is positively related to risk tolerance and more bullish beliefs. We partition risk aversion and return beliefs into the portion predicted by the eight genetic endowments and the portion explained by everything else (i.e., the residual) to examine the importance of the eight genetic endowments in linking risk aversion and beliefs to equity market participation. Our estimates suggest that the eight genetic endowments associated with cognition, personality, health, and body shape can explain about a third of the relation between a person's risk aversion and return beliefs and their equity market participation.

We similarly estimate the role of the genetic endowments in linking the investor characteristics to the economic outcomes. Specifically, we estimate the relation between each of the economic outcomes and the portion of the characteristic (e.g., trust) predicted by the individuals' eight genetic endowments versus the portion explained by everything else. We find that a substantial amount of the relation between economic outcomes and investor characteristics can be attributed to the portion of the characteristic predicted by this set of genetic endowments. For instance, the portion of trust predicted by the eight genetic scores accounts for 43% of the R^2 in a regression of stock market participation on the variation in trust predicted by the eight genetic endowments and the variation in trust attributed to everything else.

Our results have a number of implications. First, our tests help explain how and why stock market participation, risk aversion, and return beliefs have heritable components—all of these economic outcomes are related meaningfully to genetic endowments associated with cognition, personality, health, and body shape. Further, the genetic endowments link the heritability literature with the investor characteristics literature as all of the investor characteristic variables previously shown to explain stock market participation are predicted by the genetic endowments. Thus, stock market participation heritability arises, at least in part, because the genetic endowments influence the realized characteristics and the characteristics help explain variation in risk aversion, equity market beliefs, and stock market participation. For example, a higher genetic endowment for Neuroticism predicts lower levels of trust and lower levels of trust are associated with greater risk aversion, more bearish beliefs, and lower stock market participation—all of which will therefore exhibit heritability (as will trust).

Our work also provides the first evidence that heterogeneity in beliefs regarding the *distribution* of equity returns is related to many of the investor characteristics known to explain stock market participation and has a genetic component.[3] Importantly, we consider not only an individual's expectation that the market will increase over the next year (which reveals little about one's beliefs regarding the *shape* of the distribution of expected returns), but also beliefs regarding the likelihood of a market crash (<-20% return) and a market boom (>20% return). On average, expectations regarding the distribution of expected equity returns are remarkably biased and these biases are related to genetic endowments. Further, these equity market return perceptions help explain why both genetic endowments and investor characteristics are related to market participation.

Our results also add to the understanding of genetics and individuals' financial decisions by using a different approach as well as a different sample from previous work in this area. (We compare our work to related work linking financial decisions and genetics in the next section.)

[3] In an important paper investigating wealth inequality, Barth, Papageorge, and Thom (2018) provide evidence that a genetic endowment for Educational Attainment is associated with financial sophistication (including return beliefs), and ultimately, retirement wealth. We discuss this paper in the next section.

These differences are important because a trait's heritability is not a biological constant—rather it varies from one population to another and over time.[4]

Finally, our work adds to our understanding of non-economic (behavioral economic) motivations. Cesarani, Johannesson, Magnusson, and Wallace (2012) point out that evidence of a genetic component associated with economic outcomes helps overcome the criticism that behavioral economics often lacks theory to explain heterogeneity across individuals. Related, our results can help explain why individuals respond differently to the same stimuli. For instance, consistent with previous work, we find growing up poor is inversely related to stock market participation. Nonetheless, a higher genetic endowment for Neuroticism still predicts stock market participation once controlling for growing up poor. Moreover, by investigating specific genetic endowments, we provide potential guidance/support for theory. For instance, our results tying genetic endowments associated with Neuroticism and Depressive Symptoms to risk aversion, return beliefs, and market participation, provide support for Caplin and Leahy's (2001) model that adds anxiety to the utility function. Economic choices, health, and genetics may also be related. For instance, the link between genetic scores (e.g., associated with Neuroticism and Depressive Symptoms), risk aversion, and equity return distribution beliefs is consistent with at least a partially genetic explanation for the link between reductions in stock values and increases in hospital admissions for anxiety and panic disorders (Engelberg and Parsons, 2016). From a Darwinian perspective, our results provide empirical support for the notion that biological heterogeneity in decision making, although suboptimal for a given agent, may improve the likelihood of survival for a species (e.g., Brennan and Lo, 2011, 2012; Brennan, Lo, and Zhang, 2018). Long before financial markets developed, it may have been optimal for species success to have portions of the population with innate high risk aversion and dour (bearish) outlooks and to have portions of the population with innate low risk aversion and overly optimistic outlooks.

[4] As pointed out by Campbell (2006), this may be especially important in contrast with a relatively homogenous culture such as Sweden where all households were exposed to a national financial education campaign in the late 1990s as part of the Swedish pension system reformation.

II. BACKGROUND

Understanding the factors underlying individuals' financial decisions have long been sought, with focuses on both individual characteristics and biological explanations. In an early study investigating biology and risk preferences, Harlow and Brown (1990) establish a relation between risk tolerance and participants' blood enzymes. Further analyses of the role of biology in an individual's financial decisions arise in twin studies and molecular genetics research. In this section we provide brief overviews of the previous stock market participation and closely related research, along with specific focus on the literature based on twin studies and molecular genetics.

II.A. Equity Market Participation, Risk Aversion, and Expected Return Distribution Perceptions

Traditional economic theory holds that if investors are rational, utility is solely a function of wealth, and risk aversion determines the shape of the utility function, an individual's investment decisions are (Brennan and Lo, 2011), "… completely determined by utility functions, budget constraints, and the probability laws governing the environment." Moreover, given the historical distribution of equity returns, traditional economic theory finds that most individuals should hold nearly 100% of their savings in equity (e.g., Heaton and Lucas, 1997). In contrast to the theoretical predictions, however, equity participation rates in the U.S. over the last four decades have averaged 31% when excluding IRAs, and 43% when including IRAs (Giannetti and Wang, 2016). Rates tend to be even lower for most European countries (e.g., Georgarakos and Pasini, 2011). The variation in equity market participation is usually attributed to heterogeneity in risk preferences, heterogeneity in the beliefs regarding the distribution of expected equity returns, or heterogeneity in circumstances such as trading frictions or uninsurable background risk.[5]

[5] Because traditional theory suggests investors use the same model of expected returns and incorporate all available historical information when forming expectations (e.g., see discussions in Vissing-Jorgensen, 2002; Malmendier and Nagel, 2011), investors, theoretically, have identical expectations. Previous empirical work suggests, however, that a number of factors may contribution to heterogeneity in beliefs including for example, life experience (see Benartzi, 2001; Kaustia and Knupfer, 2008; Choi, Laibson, Madrian, and Metrick, 2009; Malmendier, Tate, and Yan, 2011; Malmendier and Nagel, 2011, 2016; Cameron and Shah, 2015; Bharath and Cho, 2016; Giannetti and Wang, 2016; Knupfer, Rantapuska, and Sarvimaki, 2017; Bernile, Bhagwat, and Rau, 2017; and Anagol, Balasubramaniam, and Ramadorai, 2018; Bordalo, Gennaioli, and Shleifer, 2020).

This equity non-participation (or under-participation) puzzle has led to a large literature examining investor characteristics that explain heterogeneity in equity market participation. Consistent with individuals facing a fixed cost associated with investing in equities (e.g., Vissing-Jorgensen, 2002), stock market participation is positively related to wealth and income. Grinblatt, Keloharju, and Linnainmaa (2011) suggest, however, that fixed costs can only explain a small portion of the observed levels of non-participation. Advances in the past two decades demonstrate that equity market participation is associated with a number of additional characteristics including, for example, education, cognitive ability, trust, sociability, optimism, negative early life economic experiences, body shape, health, race, political preferences, political activism, knowing your neighbors, credit score, and ambiguity aversion.[6]

Empirical evidence also suggests investors engage in a number of presumably irrational behaviors (e.g., loss aversion). As noted in the introduction, however, theoretical models posit that innate biological differences may help explain behavioral heterogeneity—including behaviors that are irrational for the individual but optimal for species survival. For example, the objectively irrational choice to invest no wealth in equities, may seem rational to the person whose, at least partially innate, neuroticism causes them to believe equity investments are both extremely risky and have a negative risk premium.

II.B. Genetics and Individuals' Financial Decisions – Twin Studies

In the last 50 years, at least 2,700 twin studies infer the role of genetics in more than 17,800 traits by comparing phenotype differences between monozygotic ("identical") twins who have, essentially, identical DNA, and dizygotic ("fraternal") twins who, the same as any other siblings,

[6] As noted above, the equity market participation literature is very large (Google Scholar reports more than 8,000 results for "stock market participation"). We examine the most prominent variables for which we can obtain data. For evidence regarding other important characteristics—race, political preferences, political activism, knowing your neighbors, credit score, and ambiguity aversion—see, respectively, Vissing-Jorgensen (2002), Kaustia and Torstila (2011), Bonaparte and Kumar (2013), Brown, Ivkovic, Smith, and Weisbenner (2008), Bricker and Li (2017), and Dimmock, Kouwenberg, Mitchell, and Peijnenburg (2016).

share approximately 50% of the DNA that varies across humans.[7] Although requiring "some strong assumptions" (Benjamin et al., 2012), most twin studies use an established methodology to partition a phenotype's variance into three latent components—genetic, shared environment, and a residual (the non-shared environment component).[8] The genetic component estimate is denoted as the phenotype's "heritability."

In recent years, a series of studies employ Swedish Twins Registry data to estimate heritability for various financial phenotypes. Estimates of heritability from these studies include approximately 20% of risk preferences, 16-34% of overconfidence, 25% of portfolio risk choices, 33% of the variation across savings rates, and 33% of the variation in equity market participation.[9]

Although twin study results are usually presented as "nature versus nurture," the impact of genetic endowments do not remain constant because they interact with environmental effects (Dick, 2011). Therefore, heritability (usually reported as a point estimate) varies across populations and time due to these interactions. Guo (2005) points out, for example, that twins study estimates of cognitive development heritability in a society that provides equal access to education will differ greatly from the estimate of cognitive development heritability in a society where only the wealthy have access to education.

In summary, these important heritability studies estimate the proportion of an economic outcome that can be attributed to genetics for the Swedish population. We have a different goal as

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[7] See Polderman et al. (2015) for a review of twin studies. Most DNA (>99%) is identical across all humans. Thus, of the DNA that is not identical across humans, dizygotic twin siblings share approximately 50% (known as concordance).

[8] There is debate regarding the validity of heritability estimates computed from twin studies. Specifically, twin studies require an "equal environment" assumption and no assortative mating (e.g., individuals with high cognitive skills are not more likely to mate with other high cognitive skill individuals). In addition, the standard twins study methodology is typically built on the assumptions that gene effects are linear, there are no gene-gene interactions, and there are no gene-environment interactions (see Benjamin et al. (2012) and Zuk, Hechter, Sunyaev, and Lander (2012) for additional discussion). See Kamin and Goldberger (2002), and Joseph (2013) for detailed critiques of twin study inferences in the social and behavioral sciences.

[9] See Cesarini, Dawes, Johannesson, Lichtenstein, and Wallace (2009), Cesarini, Johannesson, Lichtenstein, and Wallace (2009), Cesarini, Johannesson, Lichtenstein, Sandewall, and Wallace (2010), Barnea, Cronqvist, and Siegel (2010), Cesarini, Johannesson, Magnusson, and Wallace (2012), Cronqvist and Siegel (2014), Calvet and Sodini (2014), and Cronqvist and Siegel (2015). Twin studies, including studies using Norwegian twins, have also examined other economic outcomes from parental and environmental factors (captured by birth weight) versus inherited attributes, e.g., Black, Devereux, and Salvanes (2007).

discussed in the introduction, which is to use molecular genetics to investigate *how* and *why* genetics influence financial choices. An analogy is moving from understanding that heterogeneity in life experiences can influence stock market participation (i.e., the variation in participation not due to genetics) to understanding how and why life experience influences stock market participation (e.g., living through a depression is associated with greater risk aversion).

II.C. Molecular Genetics

The human genome—the genetic information needed to build and maintain a human—is contained in 23 pairs of chromosomes (46 total, 23 from each parent) within the nucleus of each human cell.[10] Each chromosome is a tightly packed DNA molecule of the familiar double helix shape. Genes are particular regions of DNA (humans have an estimated 20,000 genes) that "code" (i.e., contain the information needed to make) proteins.[11,12] In fact, most DNA (>98%) is so-called noncoding DNA. The "rungs" of the DNA "ladder" consist of pairs of four nitrogenous bases—adenine, thymine, cytosine, and guanine, typically referred to as A, T, C, and G, where A always pairs with T, and C always pairs with G. Focusing on one side of the DNA "ladder," a single nitrogenous base (combined with the "rail" of the ladder) is denoted a nucleotide. Genome sequencing is the process of ordering these nucleotides in the genome (e.g., ATTGAC). Although the human genome contains approximately 3.2 billion base pairs, only about 0.6% vary across individuals and account for the genetic differences across individual humans.[13]

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[10] Except red blood cells (that do not have a nucleus) and germline (sperm and egg) cells that contain 23 chromosomes.

[11] For simplicity we refer to genes as the coding regions of DNA (the "classic definition"). Advances in genomic research, however, reveal that genes include non-coding portions as well (e.g., introns). As a result, there is a lack of consensus on the exact definition of a gene. An alternative, for example, is (see Keller and Harel, 2007), "A gene is a locatable region of genomic sequence, corresponding to a unit of inheritance, which is associated with regulatory regions, transcribed regions and/or other functional sequence regions."

[12] Phenotypes are also influenced by environment within the body that can, in turn, be impacted by the environment outside the body. Specifically, epigenetics examines "gene expression," i.e., which genes are activated and to what extent. In a simple analogy, DNA is hardware and epigenetics is software. Epigenetics are impacted by many factors including nutrition, sleep, aging, and exercise. Evidence suggests epigenetic impacts can be heritable. In a landmark study, for example, Katti, Bygren, and Edvinsson (2002) found that when grandfathers had excess food supply during their "slow growth period" (typically ages 9-12) just prior to puberty, grandsons suffered from increased death from heart disease and diabetes.

[13] The human genome can have other differences including insertions (extra nucleotide base pairs), deletions (missing nucleotide base pairs), copy number variants (parts of the genome include repeating patterns that can vary in the

The places where genetic sequencing differs across two individuals are known as single nucleotide variation (SNV). For instance, at a specific location within the genome (known as a locus or, plural loci), an A may be replaced with a C. When at least 1% of the population exhibits a pattern, the location is denoted a Single Nucleotide Polymorphism (SNP, pronounced "snip"). SNPs occur, on average, about once every 300 nucleotides yielding approximately 10 million SNPs in the human genome. The more common variation is denoted the major allele (e.g., adenine, A) while the less common variation is the minor allele. Because individuals have two of each chromosome (one from each parent), an individual can have 0, 1, or 2 minor alleles.

Although early molecular genetics research focused on candidate gene studies, the vast majority of current molecular genetics research focuses on Genome-Wide Association Studies (GWAS). [14,15] Despite being a relatively new approach (the first GWAS was published in 2005 (Klein et al., 2005)), it has proven highly successful: a recent review of the method in the *American Journal of Human Genetics*, concludes that "…the empirical results [associated with GWASs] have been robust and overwhelming…" (Visscher et al., 2017). Broadly, a GWAS takes an atheoretical approach and examines the relation between the phenotype and (approximately) the entire variation in the genome. This approach recognizes that most characteristics are associated with many loci that individually have small effects on the phenotype. That is, in most cases,

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number of repeats), and aneuploidy (extra or missing chromosomes). These variants are also associated with phenotypes, e.g., Down syndrome, a type of aneuploidy, results from three (rather than the usual two) copies of chromosome 21.

[14] Early molecular genetics work employed the candidate gene approach in which a researcher proposes a theoretical argument as to why specific SNPs will be related to a phenotype and then examines the relation between the phenotype (such as height) and a small set of SNPs. Unfortunately, the candidate gene approach is largely viewed as a failure as such studies suffer from an extremely high rate of false positives. One of the major limitations of candidate gene studies in social sciences is that although some rare diseases (such as sickle cell anemia) are associated with a single locus (known as a Mendelian trait), nearly all traits of interest to social scientists (e.g., neuroticism) and most medical conditions (e.g., most heart diseases) are complex and associated with many SNPs across many genes (as well as environmental factors and interactions between the two). Benjamin et al. (2012) provide an excellent summary of the pitfalls associated with the candidate gene approach. The authors reference a study by Obeidat et al. (2011), for example, that was only able to replicate results from one of 104 published candidate gene studies based on an independent sample.

[15] Most GWAS are consortium-based partnerships of multiple universities and research organizations that allow sharing of analysis for meta-analysis across samples (with pre-defined protocols) without sharing protected genotype or clinical information (see Bush and Moore (2012) for additional detail). Our discussion of meta-analysis consortium GWAS is necessarily brief and incomplete. For fuller descriptions see Visscher et al. (2017) and Evangelou and Ioannidis (2013).

outcomes are related to hundreds or thousands of SNPs. For instance, although height is highly heritable, there is no "height gene"—rather the GWAS used for height identifies 697 statistically significant SNPs across the genome.[16]

As a specific example of a GWAS, the Social Science Genetic Association Consortium (see Okbay et al., 2016) investigated 9.3 million SNPs on a discovery sample of 293,723 individuals and a replication sample of 111,349 individuals to examine the relation between the genome and educational attainment. Because the number of potential independent variables, 9.3 million, is much greater than the number of observations, researchers cannot estimate a multiple regression. As a result, a GWAS begins by regressing the phenotype on each individual SNP (and controls) and then weights the SNPs by effect size to form a single quantitative measure of the relation between the genome and a phenotype—this measure is known as a Polygenic Score (PGS, also known as polygenic risk score, genetic risk score, or genome-wide score) associated with the phenotype.

Although GWAS-based molecular genetics has become the focus of modern genetics research, interestingly, molecular genetics can only account for a fraction of heritability estimated via twin studies. Work suggests that this "missing heritability" arises from failing to adequately capture the information contained in the genome (e.g., Girirajan, 2017) and/or mismeasuring heritability in twin studies (see, e.g., Vineis and Pearce, 2011). Regardless, the missing heritability question is endemic to genetics research when comparing results from twin and molecular genetics studies.

In an important study that touches on molecular genetics and stock market participation, Barth, Papageorge, and Thom (2018) examine the relation between an Educational Attainment PGS and wealth inequality for participants in the 2006 and 2008 waves of the Health Retirement Study (HRS).[17] Although the focus of their study is understanding the relation between an Educational

[16] Because the number of examined SNPs is so large, to correct for the false positive problem, the statistical significance, or *p*-value, for a SNP is typically adjusted using a Bonferroni approach that requires rejection at the critical value associated with $p<5x10^{-8}$. That is, the height GWAS identifies 697 SNPs with *p*-values less than 0.00000005. Quick interpretations of GWAS studies usually occur with a Manhattan plot where the vertical axis is given in $\log_{10}$ scale with a critical value of 7.3 ($=\log_{10}(5x10^{-8})$).

[17] Shin, Lillard, and Bhattacharya (2018) examine the relation between a PGS for Alzheimer's Disease and saving behavior. The authors conclude that the Alzheimer's Disease PGS does not impact savings behavior or asset allocation

Attainment PGS and wealth inequality, the authors also find that the link between Educational Attainment and wealth inequality arises, in part, because their Educational Attainment PGS is positively related to stock market participation, inversely related to a measure of risk aversion, and positively associated with more accurate (i.e., smaller deviation from the historical average) beliefs regarding the likelihood of a positive market return.

Our contribution differs fundamentally from Barth, Papageorge, and Thom (2018). First, we examine a set of molecular genetic endowments associated with cognition, personality, health, and body shape and their relation with traditional economic outcomes including equity market participation, risk aversion, and beliefs regarding the distribution of equity returns. In addition, we examine the channels through which these genetic endowments can influence individuals' financial decisions. In particular, the broad range of genetic endowments—cognition, personality, health, and body shape—that we examine are plausibly associated with investor characteristics previously shown to impact equity market participation, and we focus on linking the heritability (i.e., twin studies) and investor characteristic (e.g., trust) literatures, i.e., understanding the channels that underlie stock market participation heritability, risk aversion heritability, and beliefs heritability. As a result of these differences, there is minimal overlap in the studies. For example, of the more than 1,100 coefficient point estimates we report in our empirical tests (Tables III-IX), only five overlap with estimates reported by Barth, Papageorge and Thom.[18]

III. DATA

III.A. Health Retirement Study

To obtain data on individuals' DNA as well as their life circumstances, we employ the Health and Retirement Study (HRS) survey data panel of Americans age 50 and older.[19] This age cohort

decisions after accounting for age. Brown and Sias (2019) examine the relation between technology adoption and the same PGSs we examine in this study.

[18] Specifically, both studies demonstrate an Educational Attainment PGS is positively related to stock market participation and wealth, and inversely related to risk aversion. In addition, both studies demonstrate that the relation between the Educational Attainment PGS and stock market participation is robust to inclusion of wealth and income.

[19] The Health and Retirement Study data is sponsored by the National Institute on Aging (grant number U01AG009740) and is conducted by the University of Michigan.

is important in financial markets as it accounts for at least 74% of the value of stocks and 64% of the financial assets held by individuals.[20] The HRS surveys are administered bi-annually (HRS interview "waves") between 1992 and 2016. Moreover, the sample increases over time to add new respondents (HRS "cohorts"). For example, the most recent cohort (in our data) includes individuals born between 1954 and 1959 (the "Mid Baby Boomers") while the previous cohort (the "Early Baby Boomers") includes individuals born between 1948 and 1953. Beginning in 2006, HRS selected one-half of the interviewee households (in that wave) for an "Enhanced Face-to-Face Interview" that included saliva collection (the raw source for the genetic data) as well as a "Leave-Behind Questionnaire" that included "Psychosocial and Lifestyle" questions. The 50% random enhanced face-to-face sample is rotated in every wave, i.e., Leave-Behind Questionnaire respondents in 2006 are also selected for enhanced face-to-face interviews in 2010 while those not selected in 2006 are selected for 2008 (and again for 2012, and the sample includes any new cohorts added). We use the April 2018 version (HRS v2) of the HRS PGS data that incorporates DNA from HRS participants in the extended face-to-face samples from 2006-2012 and answers by these participants to HRS surveys between 2010 and 2016. We limit our sample to respondents between ages 50 and 80. In addition, as detailed below, questions identifying an individual's beliefs regarding the distribution of stock returns (i.e., likelihood of a return less than -20% or greater than +20%) did not begin until 2010, and therefore our sample includes four HRS waves (2010, 2012, 2014, and 2016).

For households consisting of partners (e.g., husband and wife), both partners are questioned. Only one person (the household's "financial respondent"), however, answers the household financial data questions. Although some variables are measured at the household level (e.g., wealth, stock market participation), the majority of the other variables of interest, the genetic endowments, risk aversion, beliefs regarding the distribution of expected equity returns, and most of the 11 investor characteristics used in previous work (e.g., trust) are measured at the individual

[20] Using 2016 values from the Survey of Consumer Finances (https://www.federalreserve.gov/econres/scfindex.htm), these figures are based on estimates (Tables 6-89 and 1-01-16) for individuals age 55 and older (i.e., the SCF age breakpoint).

level. Therefore, we limit our analysis to financial respondents. Nonetheless, in the Internet Appendix, we repeat our tests incorporating genetic endowments for both spouses when examining (household) stock market participation and find similar results.[21]

III.B. Outcomes – Stock Market Participation, Risk Aversion, and Expected Return Distribution Perceptions

We select three economic outcomes that result from, or influence, individuals' financial decisions: equity market participation, risk aversion, and return beliefs. To measure equity market participation we generate two variables from the HRS data—an indicator for holding equity (either directly or in retirement/IRA/Keogh accounts) and the fraction of financial wealth in equities (both directly held and in retirement/IRA/Keogh accounts).[22] Note that given the structure of the HRS interviews, in some cases we can observe if the respondent participates in equity markets, but cannot estimate the fraction of wealth invested in equity.[23] Appendix A provides details of the construction of these measures.

We assess risk aversion through the following question asked in the 2014 and 2016 HRS waves: "Are you generally a person who tries to avoid taking risks or one who is fully prepared to take risks? Please rate yourself from 0 to 10, where 0 means 'not at all willing to take risks' and 10 means 'very willing to take risks.'" To compute our risk aversion measure (used for the 2010-

[21] One concern may be whether surveys adequately capture individual characteristics, beliefs, and behaviors. For example, in assessing individual beliefs regarding the likelihood of a positive or negative stock market return, individuals tend to report round numbers (e.g., 30% rather than 29%) when estimating probabilities. Similarly, measures of individual characteristics, such as trust, are generated via responses to a series of questions regarding trust (as one cannot view "trust"). Nonetheless, because most of the characteristics used to help explain heterogeneity in equity market participation are measured with error (e.g., trust, sociability), work in this area is necessarily based on less than perfect measures. As a robustness check, we also estimate our primary test based on the average outcome for each individual, e.g., the average predicted probability of the market falling by more than 20% for each individual. As detailed in the Internet Appendix, our results remain nearly identical. We thank Stephen Siegel for suggesting this test.

[22] Because much of the work in equity market participation focuses on earlier surveys that lack sufficient data to infer equity holdings in retirement (pension/IRA/Keogh) funds, as a robustness test, we repeat our analysis focusing only on direct holdings (i.e., excluding retirement funds). Results, reported in the Internet Appendix, are essentially unchanged.

[23] For example, a respondent may report they have direct holdings in equity, but when queried about the value, they may respond they do not know, or refuse to answer.

2016 sample period), we average each respondent's score to this question over years 2014 and 2016 and subtract the average from 10 (so that higher values indicate greater risk aversion). As detailed below, we use a standardized (i.e., rescaled to zero mean, unit variance) version of this measure in our empirical tests for ease of interpretation.[24]

We use three questions to measure respondent beliefs about the distribution of expected returns. Starting in 2002, the HRS asked respondents, "We are interested in how well you think the economy will do in the future. 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?"[25] Beginning in 2010, HRS added two questions regarding the *distribution* of expected stock returns. Specifically, the first question asks, "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 have gained in value by more than 20 percent compared to what they are worth today?" The second question asks the probability for the other side of the distribution, i.e., the percent chance stocks "… have fallen in value by more than 20 percent …?"[26]

[24] As detailed in the Internet Appendix, we also consider a measure of relative risk aversion (inferred from "income-gamble" questions asked in earlier waves) and find similar results. We focus on self-rated risk aversion because (1) research suggests such questions better capture risk aversion (Kapteyn and Teppa, 2011; and Guillemette, Finke, and Gilliam, 2012) relative to income gamble questions, and (2) the income gamble questions are asked between 1998 and 2006 and therefore exclude 40% of our sample.

[25] HRS has a section devoted to expectations. To ensure respondents understand the meaning, the section is introduced by "Next we would like to ask your opinion about how likely you think various events might be. When I ask a question, I'd like for you to give me a number from 0 to 100, where '0' means that you think there is absolutely no chance, and '100' means that you think the event is absolutely sure to happen. For example, no one can ever be sure about tomorrow's weather, but if you think that rain is very unlikely tomorrow, you might say that there is a 10 percent chance of rain. If you think there is a very good chance that it will rain tomorrow, you might say that there is an 80 percent chance of rain."

[26] One concern regarding probability questions is that individuals sometimes answer 50% to convey a lack of confidence in their response (see Fischhoff and Bruine de Bruin, 1999; Lillard and Willis, 2001). During our sample period, respondents who answered 50% to the question regarding the likelihood the market will increase in the next year, were asked a follow up question of whether their 50% answer meant that they believed "it is about equally likely that these mutual fund shares will increase in worth as it is that they will decrease in worth by this time next year, or are you just unsure about the chances." For those that answer they are "just unsure," HRS does not ask the latter two questions regarding the likelihood of a greater than 20% decline and a greater than 20% increase. Because our sample is limited to individuals with data for equity market participation, risk aversion, and beliefs, we exclude these individuals from our main analysis. As shown in the Internet Appendix, however, our results are essentially identical when including these individuals in the sample.

III.C. Molecular Genetic Data

We employ the polygenic scores (PGSs) computed by HRS to measure each individual's genetic predisposition for a particular trait:

$$PGS_i = \sum_{j=1}^{J} W_j G_{i,j} \qquad (1)$$

where PGS_i is the polygenic score (for a given phenotype) for individual *i*, W_j is the consortium meta-analysis GWAS weight (based on the odds ratio or beta estimates from the GWAS) for SNP *j*, and $G_{i,j}$ is HRS individual *i*'s genotype (i.e., number of reference alleles—0, 1, or 2) for SNP *j*.[27] In most cases, the GWAS weights are computed without HRS data, i.e., the HRS PGSs are out of sample estimates.[28,29] HRS scales the PGSs to zero mean and unit variance.

Because most of the GWAS weights are based on European ancestry samples (see Ware, Schmitz, Gard, and Faul, 2018) and PGSs may not be directly applicable across ancestry groups (e.g., Martin et al., 2017), we limit our sample to European ancestry individuals.[30] In addition, even within a given ancestry, "population stratification" can contaminate results. Population stratification occurs when individuals in the same sample differ in SNP frequency, e.g., because SNPs are hereditary, Southern Europeans may exhibit a SNP more often than Northern Europeans (the underlying cause is non-random mating usually driven by physical separation between the groups). This can lead to complications when environmental factors impact phenotypes. The most

[27] Beauchamp et al. (2011) point out that both theory and evidence from animal breeding and behavioral genetics supports the use of the simple linear additive model that has become standard in molecular genetics research.

[28] HRS participates in several of the GWAS consortiums. In almost all of these cases, however, HRS data are excluded prior to generating the weights used to compute the HRS PGSs. Per correspondence with HRS, the PGS associated with BMI is the only PGS that includes the HRS sample in computing the GWAS weights used by HRS. The HRS sample, however, contributes less than 3% of the BMI GWAS observations (see Ware, Schmitz, Gard, and Faul, 2018).

[29] We use the PGSs computed by HRS. All PGSs are a function of the sample and weights computed by the consortium (e.g., better PGSs for a given phenotype will be found over time as the consortium sample size increases). Moreover, computation of the PGS requires the researcher (in this case, HRS) to make a number of decisions regarding the method, e.g., whether to include only highly statistically significant SNPs, or all SNPs. HRS, for example, includes all available SNPs in their estimate as recent work (e.g., Simonson, Willis, Keller and McQueen, 2011; Abraham, Kowalczyk, Zobel, and Inouye, 2013; Abraham and Inouye, 2014; Goldstein, Yang, Salfati, and Assimes, 2015; Abraham et al., 2016; Ware et al., 2017) suggests that doing so produces better (out of sample) predictions. Because PGSs depend on both the consortium sample and the construction method, our HRS computed Educational Attainment PGS is different than the Educational Attainment PGS used by Barth, Papageorge, and Thom (2018).

[30] In addition, the outcome variable of risk aversion has been found to vary across populations (Falk, Becker, Dohmen, Enke, Huffman, and Sunde, 2018).

popular way to solve this issue is to include SNP principal components in the analysis that, theoretically, capture within sample variation in SNPs. As such, HRS provides the first 10 principal components for the HRS European ancestry sample. Following the guidance in Ware, Schmitz, Gard, and Faul (2018), we include all 10 HRS SNP principal components in our tests.

A related concern is that, by definition, an individual's DNA is correlated with their parents' DNA and therefore the PGSs may capture variation in social circumstances. However, because the PGSs are based on weights computed out of sample, this would only be a valid concern if the phenotype is related to the same genotypes across different parents—this could occur if the underlying genetic population stratification is correlated with phenotypic social stratification. For example, perhaps immigrants sharing a common ancestry are more likely to have lower educational attainment due to a bias against their ancestry group. Note that, at least theoretically, the principal components should capture these effects. Perhaps more important and inconsistent with the hypothesis that the PGSs capture social stratification, work suggests that the ability of PGSs to predict variation across individuals is largely unchanged even when controlling for family fixed effects. Domingue et al. (2015) report, for example, that an Educational Attainment PGS's ability to discriminate among siblings is approximately the same magnitude as its ability to discriminate across non-related individuals.

Although the HRS data include PGSs for 29 phenotypes, we focus on a smaller set based on previous evidence of relations between individual characteristics (i.e., phenotypes) and equity market participation.[31,32] We select two PGSs from each of the four broad genetic classifications we examine (cognition, personality, health, and body shape). First, given evidence that cognition metrics (both measured cognition and realized education levels) are positively related to equity market participation (e.g., Kezdi and Willis, 2003; Benjamin, Brown, Shapiro, 2013; Christelis, Jappelli, and Padula, 2010; Grinblatt, Keloharju, and Linnainmaa, 2011; Cole, Paulson and

[31] For completeness, the Internet Appendix provides our primary tests for the additional 21 PGSs.
[32] Because risk aversion and beliefs are complex characteristics, they are likely related to multiple genetic endowments. See Kamstra, Kramer, and Levi (2012) for discussion of the evidence linking risk aversion to depression and Nicholson, Soane, Fenton-O'Creevy, and Willman (2005) for evidence linking risk aversion to neuroticism.

Shastry, 2014), we include each respondent's genetic endowments related to cognition (the Educational Attainment PGS and the General Cognition PGS). Second, given personality traits such as trust, sociability, and optimism are associated with equity market participation (e.g., Hong, Kubik, and Stein, 2004; Puri and Robinson, 2007; Guiso, Sapienza, and Zingales, 2008; Heimer, 2014; Balloch, Nicolae, and Philip, 2015; Giannetti and Wang, 2016), we include two genetic endowments related to personality characteristics (the Neuroticism PGS and the Depressive Symptoms PGS). Third, given observed health is positively associated with equity market participation (e.g., Rosen and Wu, 2004; Yogo, 2016) and that heart disease is the leading cause of death in the U.S., we include the two genetic endowments associated with heart disease (the Myocardial Infarction PGS and the Coronary Artery Disease PGS). Finally, given evidence that body shape is associated with equity market participation (BMI is negatively associated with market participation and height is positively associated with participation; Addoum, Korniotis, and Kumar, 2017), we include participant's BMI PGS and Height PGS. Appendix A provides details regarding the construction of the HRS PGSs.[33]

III.D. Investor Characteristics Previously used to Explain Stock Market Participation

Beyond the genetic endowment variables we also consider 11 investor characteristics that previous work suggests can help explain equity market participation (via their impact on risk aversion, beliefs, or circumstances): wealth, income, education, cognitive ability, trust, sociability, optimism, negative early life economic experiences, height, BMI, and health. Although a number of previous studies use HRS data, the survey has evolved over time, and because we focus on recent data our measures are often more direct than earlier measures, e.g., more recent surveys include psychosocial questions directly focused on measuring trust and optimism. Appendix A

[33] A reader may logically ask why we focus on genetic endowments for cognition, personality, health, and body shape rather than estimating genetic endowments for equity market participation, risk aversion, and beliefs directly. As detailed above, a GWAS requires a very large sample size due to the highly polygenetic nature of most phenotypes, i.e., our sample size is much too small to estimate a PGS. For instance, the Educational Attainment GWAS is based on a sample size of more than 405,000 individuals. In addition, by focusing on GWAS weights estimated over different (i.e., non-HRS) data, our PGSs are out-of-sample estimates.

provides details regarding the construction of each of these 11 characteristics as well as a brief description of the proposed mechanism (from previous studies) linking the characteristic to equity market participation, risk aversion, and beliefs (and at least one associated reference). We also include control variables in our analyses. Specifically, we include indicators for HRS waves, respondent age, gender, retired, and married. Appendix A provides details regarding construction of the control variables.

III.E. Descriptive Statistics

For an individual's observations to be included in the sample requires data on the respondent's genetic endowment, stock market participation, risk aversion, return beliefs, household wealth and income, age, gender, and marital and retirement status. Our final sample consists of 5,130 individuals and 13,200 individual-year observations over four HRS waves (2010, 2012, 2014, and 2016). Our respondents are approximately equally likely to be male or female, the average age is 66, 49% are retired, and 61% are married.

Tables I and II report descriptive statistics and correlation coefficients for the economic outcome variables, the genetic data (PGSs), and the 11 investor characteristics used in previous studies. Some of the variables, such as PGSs, are observed at the respondent level while others, such as stock market participation are overserved at the respondent-survey wave level (see Appendix A). The values in Tables I and II are based on the pooled sample used in our analysis, i.e., there are 5,130 unique Neuroticism PGS observations and the average respondent's equity market participation and beliefs regarding the distribution of expected equity returns is observed in 2.6 survey waves implying 13,200 total observations.

[Insert Tables I and II about here]

Panel A in Table I reports the descriptive statistics for the economic outcome variables and shows that 59% of the respondents in our sample hold some equities and the average household in our sample has 37% of their financial assets in equities.[34,35] The third row reveals substantial variation in self-rated risk aversion with a standard deviation of 2.06 on a scale of 0 to 10. As noted above, we use a standardized version (fourth row) of this variable throughout the empirical analysis for ease of interpretation. The last three rows report respondent beliefs regarding the likelihood that the market will increase, rise by at least 20%, and fall by at least 20% over the next year.[36] Although a broad literature examines equity participation and a number of studies also evaluate risk aversion, comparatively little work focuses on understanding heterogeneity in beliefs regarding the distribution of expected equity returns because, prior to our sample period, few surveys questioned individuals regarding their beliefs (especially perceptions related to the likelihood of an extreme gain or loss). Consistent with previous work, however, the values reported by respondents differ greatly from the historical distribution of equity returns.[37] Specifically, between 1927 and 2016, rolling 12-month U.S. equity returns averaged 11.9% with a standard deviation of 21.3%. Nearly identical to the expected values under a normal distribution, 73.9% of the historical annual returns were positive, 33.8% were greater than 20%, and 6.6% of the observations were less than -20%. The typical individual, however, is much too bearish relative to the historical distribution—the average individual greatly underestimates the likelihood of the market increasing (mean estimate of 47% versus 74% historically) and greatly overestimates the likelihood of a 20% or greater decline in stock prices (mean estimate of 30% versus less than 7%

[34] As shown in Table I, a few individuals have more than 100% of their financial wealth invested in equities which typically occurs when individuals have retirement savings invested in equity, but non-retirement financial wealth (e.g., debt) is negative. As detailed in Appendix A, we winsorize the fraction of wealth held in equities at the 99% level.

[35] We find that 30% of respondents hold equity directly (i.e., excluding retirement funds) consistent with estimates reported in earlier studies using the survey questions on direct holdings (e.g., Addoum, Korniotis, and Kumar (2017) report 29% of HRS households hold equity based on the 1992-2008 HRS waves). Consistent with recent evidence (e.g., Giannetti and Wang, 2016), the results demonstrate that equity market participation estimates are substantially greater (at least in recent years) when including equities held in retirement accounts.

[36] We treat beliefs regarding the likelihood of a greater than 20% fall in equity prices as a measure of an individual's view of the perceived riskiness of equity investing. We recognize, however, that such beliefs may also relate to risk aversion or ambiguity. For example, as Malmendier and Nagel (p. 381, footnote 6, 2011) point out, an investor with optimistic beliefs might also naturally report less risk aversion. Dow and Werlang (1992) examine how ambiguity can impact portfolio decisions.

[37] Several studies find that individuals tend to underestimate the likelihood of the market increasing in the next year, e.g., Dominitz and Manski (2007, 2011), Hurd and Rohwedder (2012), Hurd, van Rooij, and Winter (2011). In addition, Goetzmann, Kim, and Shiller (2017) show that both individual and institutional investors greatly overestimate the likelihood of an extreme one-day stock market crash.

historically). Individuals, on average, are closer to the historical value for the likelihood of a 20% or greater market gain (mean estimate of 27% versus 34% historically).

Panel B of Table I reports the correlations between the economic outcome variables. Consistent with theory, equity market participation (first column) is inversely related to risk aversion, positively related to an individual's beliefs regarding the likelihood that markets will rise, and inversely to beliefs regarding the likelihood of a market crash, but less strongly related to beliefs regarding the likelihood of a market boom. Consistent with recent work (Lee, Rosenthal, Veld, and Veld-Merkoulova, 2015), risk aversion is inversely related to individual's beliefs regarding the expected likelihood of a positive market return.

Panels C and D in Table I report descriptive statistics and correlations for the genetic data. By construction, the HRS PGS scores are standardized.[38] As expected, the "pairs" of PGS measures are related, yet not redundant, e.g., the correlation between the General Cognition PGS and the Educational Attainment PGS is 0.27.

Table II reports descriptive statistics and correlations for the 11 investor characteristics. Many of the factors known to explain equity market participation are strongly related to each other. For example, consistent with Guiso, Sapienza, and Zingales (2008), trust is positively associated with sociability and consistent with Hong, Kubik, and Stein (2004), sociability is positively related to education.

IV. PGSs, Equity Market Participation, Risk Aversion, and Beliefs

IV.A. Do Genetic Endowments Predict Economic Outcomes?

We begin by examining whether the eight molecular genetic endowments for cognition, personality, health, and body shape help explain variation in the economic outcome variables. Our hypotheses are based on extant literature that relates heterogeneity in investor characteristics to

[38] The PGSs provided by HRS are standardized. Because, however, not all individuals included in the HRS genetic dataset have sufficient information to be included in our sample we re-standardize (rescale to zero mean, unit variance) the HRS genetic data for our sample to ensure the mean and variance are exactly zero and one, respectively.

heterogeneity in equity market participation.[39] First, given evidence that education and cognitive ability are positively associated with equity market participation, we hypothesize that PGSs associated with Educational Attainment and General Cognition predict greater stock market participation and consequently may also predict lower risk aversion, a higher perceived likelihood of a positive market return, and a lower perceived likelihood of a 20% or greater decline in stock prices. Although individuals, on average, underestimate the likelihood that the market will increase by more than 20%, they also greatly overestimate the likelihood of a negative market return and a greater than 20% decline in stock prices. Thus, we expect higher Educational Attainment and General Cognition PGSs will predict a more realistic view of the standard deviation of expected returns and, therefore, a lower perceived likelihood of a greater than 20% increase in equity prices.

Second, given evidence that trust, sociability, optimism, and good health are positively associated with equity market participation, we hypothesize that PGSs associated with Neuroticism and Depressive Symptoms, and PGSs associated with poor health—Myocardial Infarction and Coronary Artery Disease—predict decreased equity market participation, and similarly predict higher risk aversion, lower perceived probability of a positive market return, and higher perceived probabilities of a greater than 20% decline or rise in equity prices. Last, given evidence that lower BMI and greater height are positively related to equity market participation, we posit that a smaller BMI PGS and larger Height PGS predict greater market participation, lower risk aversion, higher expectations of a positive market return, and lower perceived probabilities of an extreme (>±20%) market return.

Panel A in Table III reports the results of panel regressions of the economic outcome variables on each of the eight PGSs individually, the 10 HRS genetic principal components, and the control variables (indicators for HRS waves, age, gender, retired, and married). Standard errors are clustered at the respondent level (throughout the paper). To conserve space, we only report the coefficients associated with each of the PGSs variables. Thus, Panel A reports the results from 48

[39] See Section III.D and Panel C of Appendix A for details including a brief description of the proposed channels and associated references.

different regressions (six outcomes times eight PGSs). Given the PGSs are standardized, the coefficients in Table III reflect the relation between a one standard deviation change in the PGS and the outcome variable. For instance, according to the first cell in the table, a one standard deviation increase in the Educational Attainment PGS is associated with a 7.1% higher likelihood (statistically significant at the 1% level) that an individual holds any equity.[40]

[Insert Table III about here]

The results in Panel A provide strong support for our hypotheses: genetic endowments associated with cognition, personality, health, and body shape predict equity market participation, risk aversion, and investor beliefs regarding the distribution of expected equity returns. Specifically, 46 of the 48 reported coefficients have the expected sign and, of those 46 coefficients, 31 differ materially from zero at the 10% level or better (two-tail tests). Neither of the two coefficients with an unexpected sign differ materially from zero at the 10% level.

Although we have shown that the PGSs are correlated, and multicollinearity is an issue, we next include all eight PGSs (along with the control variables and 10 genetic principal components) in a single regression for each of the economic outcome variables. Panel A of Table III shows that when predicting stock market participation (first column) and including each of the genetic factors by themselves as an independent variable, all were statistically significant. Panel B shows that when all eight PGSs are included in the same regression, some of the PGS have stronger effects than others. The Educational Attainment PGS remains strongly related to most of the economic outcomes, even when all PGS are included. For example, stock market participation is most strongly related to the Educational Attainment PGS—a one standard deviation greater Educational Attainment PGS predicts a 6.0% greater likelihood of holding any equities. Similarly, the Neuroticism PGS still significantly predicts four of the six economic outcomes with risk aversion being most strongly related to the Neuroticism PGS—a one standard deviation greater Neuroticism

[40] We focus on linear probability models for ease of interpretation, to facilitate comparison with much of the literature in this area (e.g., Hong, Kubik, and Stein, 2004; Puri and Robinson, 2007; Giannetti and Wang, 2016; Barth, Papageorge, and Thom, 2018), and for our later focus on comparing the relative contributions from these eight genetic endowments and all other sources of variability. In the Internet Appendix, we repeat our tests with limited dependent variable models (binary logit and fractional logistic) and reach essentially identical conclusions.

PGS predicts a 6.4% standard deviation higher risk aversion (recall the risk aversion measure is scaled to unit standard deviation).

Nonetheless, even when accounting for an individual's genetic predisposition for Educational Attainment and Neuroticism, we still find other PGS to contain predictive powers. For example, stock market participation is at least marginally predicted by the Depressive Symptoms PGS, the Myocardial Infarction PGS, and the BMI PGS. Thus, each of the four genetic component groups we examine—cognition, personality, health, and body shape—appear to impact equity market participation in the hypothesized directions. The table also shows that when we include all eight PGSs, heterogeneity in beliefs regarding the distribution of equity returns remain related to a number of genetic factors and usually in the expected directions. (The one exception is that beliefs regarding the likelihood of a market increase are positively related to the Coronary Artery Disease PGS (at the 5% level), inconsistent with our priors. The results suggest, for example, that a one standard deviation higher Myocardial Infarction PGS predicts an approximately 1.37% lower value for beliefs regarding the likelihood of the market increasing in the next year. Given the standard deviation of the dependent variable is 26.72% (see Table I), this represents a 5.1% standard deviation shift (i.e., 1.374/26.717=0.051).

IV.B. Do the PGSs Predict Equity Market Participation when controlling for Risk Aversion and Beliefs?

The results in Table III show that genetic endowments associated with cognition, personality, health, and body shape predict an individual's stock market participation, risk aversion, and beliefs. Given stock market participation should be a function of risk aversion and beliefs, we next examine whether the ability of these genetic endowments to predict risk aversion and beliefs can fully explain why these endowments predict stock market participation. Our approach is straightforward—we add risk aversion and beliefs as independent variables to the regression of stock market participation on each of the PGSs. If genetic variation in self-reported risk aversion and beliefs fully capture the variation in equity participation predicted by the PGS, then the coefficient associated with the PGS should no longer differ meaningfully from zero.

We report the results from this analysis in Table IV. The first and third columns in Table IV report the coefficients associated with each PGS from separate regressions of each equity market participation measure on each PGS (individually), risk aversion, the three return belief metrics, the first 10 principal components of the genetics data, and the control variables (indicators for HRS waves, age, gender, retired, and married). For ease of comparison, the second and fourth columns report the coefficients associated with each PGS without adding risk aversion and return beliefs as regressors (i.e., the values from the first two columns of Panel A in Table III). The results provide strong evidence that the PGSs continue to predict stock market participation even after accounting for risk aversion and beliefs. Although the coefficients are generally smaller—suggesting that at least some of the relation between these eight genetic endowments and stock market participation arises from the genetic endowment's relation with self-reported risk aversion and return beliefs—the coefficients remain substantial and statistically significant. For example, Column (1) of Table IV shows that when we account for the variation in market participation explained by contemporaneously-measured risk aversion and return beliefs, a one standard deviation higher Neuroticism PGS is associated with a 2.8% lower likelihood of holding equity (statistically significant at the 1% level). The previous PGS only regression from Table III reported in Column (2) of Table IV indicates that the same Neuroticism shock predicts a 3.7% lower likelihood of holding equity before controlling for risk aversion and beliefs.

[Insert Table IV about here]

Two non-mutually exclusive explanations exist for why these genetic endowments continue to predict stock market participation once accounting for risk aversion and beliefs. First, as Harlow and Brown (1990) suggest, adding biological data to traditional measures of risk aversion (or beliefs) should generate better estimates of risk aversion (or beliefs). That is, any measure of risk aversion and beliefs is less than perfect—thus these PGSs may continue to predict stock market participation because they capture dimensions of risk aversion and beliefs not fully reflected in self-reported values. Second, as discussed earlier, PGSs have the ability to capture factors other than risk aversion and beliefs, such as variation in circumstances, that influence stock market participation.

V. PGSs, Investor Characteristics, and Economic Outcomes

V.A. Investor Characteristics and Economic Outcomes

In this section we examine the extent to which the eight genetic endowments can link the investor characteristics literature with the heritability literature by investigating the channels through which these endowments predict stock market participation, risk aversion, and return beliefs. We begin by evaluating the relations between the economic outcome variables and each of the 11 investor characteristics that have been documented in previous work to explain equity market participation. Because many of the characteristics are strongly correlated and our goal is understanding the role of the genetic endowments in explaining previously identified relations (rather than determining which of the investor characteristics best explains the outcome variables), we focus on panel regressions of the outcome variables on each of the investor characteristics individually while controlling for HRS waves and respondent demographics (gender, age, married, and retired). In addition, for ease of interpretation and comparison, we standardize (i.e., rescale to zero mean, unit variance) each of the characteristics. The coefficients for each of the individual investor characteristics from the 66 panel regressions (11 characteristics times six outcomes) are reported in Panel A of Table V.

[Insert Table V about here]

Consistent with previous work, equity market participation is positively related to wealth, income, education, cognition, trust, sociability, optimism, height, and health and negatively related to early life poverty (*poor*) and BMI. As shown in the third column, we also find risk aversion to be related to each of these 11 characteristics that have been used in previous work to explain equity market participation. Moreover, the relationships are all in the expected direction and statistically significant. Specifically, greater wealth, income, education, cognition, trust, sociability, optimism, height, and health are associated with a lower risk aversion. Conversely, higher BMI and growing up poor are positively associated with risk aversion.

The last three columns in Table V report the relations between the 11 individual characteristics and return beliefs. This is largely new territory—few studies examine if these characteristics are related to variation in investor beliefs regarding the likelihood of a positive return, and, as far as we are aware, no published study examines whether these characteristics may be associated with variation in beliefs regarding the shape of the distribution of expected returns, i.e., the likelihood of a large gain (>20%) or loss (<-20%). The results in the fourth column document that all 11 characteristics are meaningfully related to beliefs regarding the likelihood of a market increase (in the expected direction) consistent with the hypothesis that these investor characteristics correlate with equity market participation, at least in part, because they reflect heterogeneity in return beliefs as well as heterogeneity in risk aversion. The results in the last two columns provide important and intuitive insights as well. First, as noted above, because individuals, on average, greatly overestimate the riskiness of the market, we expect lower probabilities of at least a 20% gain associated with more realistic views of the standard deviation of equity returns. Consistent with our hypothesis, cognition and height are negatively associated with beliefs regarding the likelihood of a market boom (>20%). Trust, optimism, and health, however, are positively related to variation in perceptions regarding the likelihood of a boom. Given respondents, on average, greatly overestimate the likelihood of a market crash (<-20%), we expect variables associated with a better understanding of equities, such as cognition or education, to be negatively associated with beliefs regarding the likelihood of a crash, while the "negative" variables (BMI and early life poverty) should be positively associated with beliefs regarding the likelihood of a crash. The results in the last column confirm this pattern. Specifically, 10 of the 11 characteristics have the expected sign (the lone exception being the insignificant coefficient for height) and nine of the 11 are statistically significant at the 5% level or better.

In sum, the results in Panel A show these 11 investor characteristics are related to equity market participation, at least in part, because they are associated with both heterogeneity in risk aversion and heterogeneity in beliefs regarding the distribution of equity returns. For instance, individuals with high trust are more likely to participate in equity markets (first two columns), are less risk averse (third column), and their beliefs regarding the distribution of expected equity returns are shifted to the right (final three columns).

Because the independent variables are standardized in both Tables III and V, we can directly examine the relative magnitude of the relation between the eight genetic endowments (established at least 50 years prior to the outcomes) and the economic outcomes versus the relation between the 11 investor characteristics (that are observed, approximately, at the same time as the outcomes) and the economic outcomes. For example, the average absolute value of the coefficient in the third column of Panel A in Table V indicates that a one standard deviation change in the average investor characteristic is associated with a 12.6% standard deviation change in risk aversion. The average absolute value in the third column of Table III Panel A is 3.6%. Thus, on average, the relation between risk aversion and the average genetic endowment in our set (measured more than 50 years prior) is 28% of the relation between risk aversion and the average contemporaneously-measured investor characteristic (i.e., 0.036/0.126=0.282). Results are similar across the two equity participation variables (i.e., the average absolute value in the first two columns of Table III are 28.8% and 29.2%, respectively, of the average absolute value of the first two columns in Panel A of Table V). The relations for the three measures of beliefs regarding the distribution of expected equity returns and the average of these eight genetic endowments range from 26% to 95% of the relation between the beliefs regarding the distribution of expected equity returns and the average of the 11 investor characteristics.

For completeness, we also report in Panel B of Table V the results for an analysis in which we include all 11 investor characteristics in the model simultaneously (along with the controls for gender, HRS wave, age, retired, and married). Our results are not directly comparable to previous work because: (1) we include different combinations of explanatory variables (e.g., because it had yet to be "discovered," Hong, Kubik, and Stein (2004) do not include trust in their tests), and (2) many of our metrics, although measuring the same construct, differ from the measures used in earlier studies. As noted above, for instance, advances in the HRS survey allow for, arguably, substantially improved measures of variables such as trust and optimism. Regardless, the results in Panel B of Table V largely support previous work. For example, the first column shows that equity market participation is positively related to wealth, income, education, cognition, trust, and health, and is inversely related to early life poverty. Analogously, risk aversion (third column of Panel B) is negatively related to income, education, sociability, optimism, height, and health.[41]

V.B. Do Genetic Endowments Predict Investor Characteristics?

Having shown the consistency of our work with previous studies, we now provide novel insights by examining the extent to which genetic endowments associated with cognition, personality, health, and body shape predict heterogeneity in the 11 investor characteristics. Specifically, we estimate panel regressions of each investor characteristic on the control variables (indicator variables for HRS waves, gender, age, married, and retired), the 10 HRS genetic principal components, and each of the individual PGSs. For ease of interpretation, we standardize (rescale to zero mean, unit variance) each of the 11 dependent variables. Table VI Panel A reports the results. Thus, for example, the first cell implies that a one standard deviation higher Educational Attainment PGS predicts a 12.9% standard deviation higher log wealth.

[Insert Table VI about here]

The results in Table VI provide strong evidence that all 11 characteristics identified in previous work are meaningfully related to genetic endowments associated with cognition, personality, health, and body shape. Moreover the signs of the relations are intuitive. Wealth, for example, is positively predicted by the Educational Attainment and Height PGSs and inversely predicted by the Neuroticism, Depressive Symptoms, Myocardial Infarction, Coronary Artery Disease, and

[41] Inconsistent with the tests in Panel A, however, risk aversion is positively related to trust when including the other 10 investor characteristics in the model. Moreover, the investor characteristics are largely associated with the return beliefs in the expected direction (with a few exceptions such as a positive relation between BMI and beliefs regarding the likelihood of a market increase) when including all 11 characteristics simultaneously. For example, lower wealth, lower trust, and lower health are all associated with beliefs that a severe (greater than 20%) market decline in the next year is more likely.

BMI PGSs. In fact, every investor characteristic is meaningfully related to at least three of the eight PGSs and the average characteristic variable is meaningfully related to 5.7 of the eight PGSs.

Panel B of Table VI repeats the analysis but regresses each of the 11 investor characteristics on all eight PGS (in addition to the control variables and 10 HRS genetic principal components) simultaneously. The average investor characteristic is meaningfully predicted by 3.3 of the PGSs in the multiple regression framework. Once again, the signs of the relations are largely intuitive. Optimism, for instance, is positively related to the Educational Attainment PGS but negatively related to the PGSs associated with Neuroticism, Depressive Symptoms, Myocardial Infarction, and BMI. In sum, the results in Table VI provide strong evidence that variation in all 11 of these investor characteristics is driven, at least in part, by genetic endowments associated with cognition, personality, health, and body shape.

V.C. Investor Characteristics and PGS Channels

The tests thus far do not include the eight genetic endowments and 11 investor characteristics as independent variables in the same regression because investor characteristics represent both genetic and environmental sources of investor heterogeneity, i.e., the characteristics are contemporaneous realizations of an investor's state while the PGSs are predictors determined at conception. That is, the characteristics may, at least in part, serve as the channels linking the PGSs to the economic outcomes (stock market participation, risk aversion, beliefs). Thus, we next examine the data to identify characteristics that may serve as channels for each of eight genetic endowments. Our approach is straightforward—we perform a sensitivity analysis to examine if adding the investor characteristic to the regression subsumes the predictive relation between the PGS and the economic outcome. For instance, if the Height PGS predicts stock market participation because taller individuals are more likely to hold equity, then adding realized height to the regression will subsume the ability of the Height PGS to predict participation. Of course, realized height reflects both the genetic predisposition for height, environmental factors that impact height (e.g., nutrition), as well as potential interactions.

For ease of comparison, the first column in Panel A of Table VII reports the coefficient associated with each PGS from regressions of stock market participation on the PGS, the 10 genetic principal components and the control variables (i.e., this column is identical to the first column of Panel A in Table III). The remaining columns report the coefficient associated with the PGS when including the investor characteristic listed in the column heading. For example, as shown in the second column, once accounting for realized wealth (by adding realized wealth as a regressor), a one standard deviation higher Educational Attainment PGS predicts a 4.2% increase in the likelihood of holding any stock. This can be compared to the coefficient in the first column in which a one standard deviation higher Educational Attainment PGS predicts a 7.1% increase in the likelihood of holding any equity. Thus, the reduced magnitude of the PGS coefficient suggests that the Educational Attainment PGS predicts stock market participation, at least in part, because it predicts wealth and wealth is associated with greater stock market participation. Nonetheless, wealth fails to fully subsume the Educational Attainment PGS's predictive ability (i.e., the coefficient remains materially large and statistically significant at the 1% level). In short, wealth appears to be "a partial channel" linking the Educational Attainment PGS to stock market participation, but the evidence does not support the hypothesis that wealth is the sole channel linking Educational Attainment to stock market participation.

[Insert Table VII about here]

The results in Panel A provide substantial evidence of the channels linking the PGSs to stock market participation as, for every genetic endowment, there is at least one characteristic that results in considerable reductions in the absolute coefficient associated with the PGS when the investor characteristic is added to the regression. For three of the PGSs, the most intuitive directly-related characteristic appears to be a primary channel. Specifically, the General Cognition PGS no longer predicts stock market participation when controlling for a measure of realized general cognition, the Coronary Artery Disease PGS no longer predicts stock market participation when controlling for realized health, and the Height PGS no longer predicts stock market participation when controlling for realized height. Thus, for example, an individual's actual height attainment appears to be the primary channel that allows the Height PGS to predict stock market participation. Interestingly, for these three PGSs (General Cognition, Coronary Artery Disease, and Height), at least one other investor characteristic also subsumes the predictability. For example, the Coronary Artery Disease PGS also no longer meaningfully predicts stock market participation when controlling for realized wealth (perhaps not surprising given the 0.27 correlation between the wealth and health characteristics reported in Table II), suggesting that wealth may also be a channel linking the Coronary Artery Disease PGS to stock market participation.[42]

In other cases, however, none of the 11 investor characteristics (individually) fully account for the ability of the PGS to predict stock market participation. Specifically, PGSs associated with Educational Attainment, Neuroticism, Depressive Symptoms, Myocardial Infarction, and BMI continue to meaningfully predict stock market participation even when adding any of the 11 investor characteristics. For instance, the Educational Attainment PGS maintains some predictive power even when accounting for the individual's actual educational attainment and the Neuroticism PGS maintains some of its predictive power even when controlling for optimism. In short, for these five genetic endowments we find no evidence that the link between the PGS and stock market participation is subsumed by a single characteristic, suggesting additional, as yet unidentified, characteristics or combinations of characteristics link these endowments to stock market participation.[43]

Examination of the remaining panels in Table VII yields similar conclusions albeit the patterns differ. For instance, realized educational attainment does subsume the ability of the Educational Attainment PGS to predict risk aversion (Panel C). In contrast, none of the 11 investor characteristics subsume the ability of the Neuroticism PGS to predict risk aversion. In fact, for all outcomes examined in Table VII (except the likelihood of a 20% market increase), at least two of

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[42] However, despite the many studies relating health to wealth, Cesarini, Lindqvist, Ostling and Wallace (2016) do not find strong evidence of a causal relation between wealth and mortality or health care utilization.

[43] Because our focus is on identifying specific channels linking the PGSs to the outcome variables (and the fact that many of the characteristics are strongly correlated leading to a collinearity issue), we examine the relations for each of the eight PGSs by adding one characteristic at a time.

the PGSs maintain some level of predictability regardless of which of the 11 investor characteristics is added to the regression.

Overall, these results indicate that these previously identified investor characteristics are an important channel through which genetic endowments affect individuals' equity market participation, risk aversion, and beliefs concerning the distributions of stock returns.

VI. The Role of the PGS in linking Equity Market Participation, Risk Aversion, Return Beliefs, and Investor Characteristics

In our final empirical analyses, we estimate the importance of genetic endowments associated with cognition, personality, health, and body shape in linking both the economic outcomes to each other (i.e., risk aversion and beliefs to stock market participation) and the economic outcomes to investor characteristics (e.g., the relation between risk aversion and trust). As noted in the introduction, unlike molecular genetics, twin studies are well suited and important in generating estimates of phenotype heritability. Twin studies, however, cannot generate an estimate of an individual's genetic risk for a phenotype. For example, a twin study can estimate the heritability of both equity market participation and risk aversion but cannot determine whether there exist any genetic links connecting these two phenotypes or what specific genetic endowments may link the phenotypes. In contrast, because molecular genetics focuses on genetic risk scores for each individual, we can examine how phenotypes appear to be genetically linked and estimate the magnitude of these specific genetic links.

Our general research design in this section is to first remove variation in the phenotypes (both economic outcomes and investor characteristics) related to the genetic principal components and control variables, and then partition the remaining variation into the portion predicted by the eight genetic endowments and the portion attributed to everything else (i.e., the residual). For ease of exposition we denote the former the "PGS" component and the residual as the "non-PGS" component.[44] Because this approach generates predicted and residual components that are, by construction, independent, the R^2 from the second regression can be directly partitioned into the portion attributed to the eight genetic endowments and the portion attributed to everything else.

VI.A. The Role of the Eight PGSs in linking Participation to Risk Aversion and Beliefs

Given phenotypes are a function of both environment and genetics and that, in the traditional framework, heterogeneity in equity exposure is a function of risk aversion and beliefs, we begin by estimating the role of the genetic endowments associated with cognition, personality, health, and body shape in linking an individual's equity market participation to their risk aversion and beliefs. We regress each of the six economic outcome measures (the two equity market participation measures, the risk aversion metric, and the three return belief metrics) on the first 10 principal components of the genetics data and the control variables (indicators for HRS waves, age, gender, retired, and married). The residuals from these separate regressions—denoted orthogonalized outcomes—reflect variation in each economic outcome that cannot be explained by the 10 genetic principal components or the control variables.

We next regress orthogonalized stock market participation on orthogonalized risk aversion and orthogonalized beliefs. For ease of interpretation, we standardize (rescale to unit variance and zero mean) the independent variables. Panel A in Table VIII reports the estimated coefficients from the regressions of the two measures of orthogonalized equity market participation on orthogonalized risk aversion and beliefs individually (columns 1 to 4 and 6 to 9) and simultaneously (columns 5 and 10). Consistent with theory, equity market participation is negatively related to risk aversion, positively related to beliefs regarding the likelihood the market will increase in the next year, and inversely related to beliefs regarding the likelihood of a greater than 20% decline in equity markets

[44] By "everything else" we mean, of course, everything else not explained by the control variables and genetic principal components. We take this approach so that we can decompose the R^2 into PGS and non-PGS components. In the Internet Appendix we report regressions including the controls, principal components, and PGSs simultaneously and find nearly identical results (although such an approach does not allow a direct decomposition of the R^2 into PGS and non-PGS components). In addition, because the residual captures both genetic sources not captured by our eight PGSs, as well as all non-genetic sources, our estimates of the PGS share of predictability are conservative estimates of the genetic share.

over the next year regardless of whether the regressors are included individually or simultaneously. When included as the only regressor, the orthogonalized likelihood of a 20% gain is positively related to equity market participation (columns 3 and 8). However, consistent with the hypothesis that investors who view the market as less volatile are more likely to participate, when controlling for risk aversion and other beliefs, investors who believe there is a higher likelihood of a greater than 20% equity return in the next year are less likely to invest in equity markets (columns five and ten).

[Insert Table VIII about here]

We next partition the independent variables (orthogonalized risk aversion and beliefs) into PGS and non-PGS components and then estimate the following regression,

$$EQ = \beta_1 RA_{PGS} + \beta_2 RA_{Non-PGS} + \varepsilon \,, \tag{2}$$

where EQ is orthogonalized stock market participation. RA_{PGS} is the portion of orthogonalized risk aversion predicted by the eight PGSs. That is, it consists of the fitted values from a regression of orthogonalized risk aversion on the eight PGSs. (We report regression estimates in the Internet Appendix). $RA_{Non\text{-}PGS}$ is the portion of orthogonalized risk aversion independent of the eight PGSs.[45] Because the two independent variables are mechanically uncorrelated, the R^2 from equation (2) can be directly decomposed into PGS and non-PGS components:[46]

$$R^2 = \frac{\sigma^2(\widehat{EQ})}{\sigma^2(EQ)} = \frac{\sigma^2(\hat{\beta}_1 RA_{PGS})}{\sigma^2(EQ)} + \frac{\sigma^2(\hat{\beta}_2 RA_{Non-PGS})}{\sigma^2(EQ)} \,. \tag{3}$$

We then repeat this process for each of the belief metrics. We report coefficients in Panel B of Table VIII.[47] The bottom row reports the fraction of the R^2 accounted for by the portion of risk

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[45] We exclude the individual i and year t subscripts for notational brevity.
[46] For simplicity, we write Equations (2) and (3) when using only the PGS and non-PGS components of risk aversion. However, Equation (3) holds even when Equation (2) contains eight regressors, i.e., the four measures (risk aversion and the three return belief metrics) predicted by the PGSs and the four residuals. That is, given the same set of predictors (i.e., the eight PGSs), each PGS component is orthogonal to its own residual and each of the other residuals. For instance, the PGS (i.e., predicted) portion of risk aversion is orthogonal to the non-PGS (i.e., residual) portion of beliefs regarding the likelihood the market will fall by 20%.
[47] A reader may be concerned that the portion of each variable attributed to the PGS is estimated in sample and therefore PGSs captures some variation in the variable simply by chance. As a robustness test (see Internet Appendix), we repeat the analysis using out-of-sample estimates and find essentially identical results.

aversion or beliefs predicted by the genetic endowments, i.e., the first term on the right-hand side of Equation (3) divided by the R^2.

The results in Panel B suggest that a substantial portion of the relation between individuals' equity market participation choices and their risk aversion or beliefs arises from the genetic endowments associated with cognition, personality, health, and body shape. For example, focusing first on the regressions that include only the PGS and non-PGS components of a single risk aversion or return belief variable (i.e., columns 1-4 and 6-9), all coefficients (both the portion predicted by the eight PGSs and the portion attributed to everything else) are statistically significant at the 1% level and economically meaningful. For instance, the first column reveals that a one standard deviation increase in PGS-predicted risk aversion is associated with a 5.4% smaller chance of holding equity while a one standard deviation increase in non-PGS risk aversion is associated with a 5.0% lower chance of holding equity. For three of the four variables (risk aversion, perceived likelihood that the market will increase over the next year, and the perceived likelihood that the market will fall by at least 20% over the next year), the signs of the PGS and non-PGS portions match across the eight regressions, and the portion predicted by the eight PGSs, on average, accounts for 42% of the regression R^2 (i.e., the average value in the bottom row across columns 1, 2, 4, 6, 7, and 9 is 42%).

Similar to Panel A, columns 3 and 8 show the uniqueness of the regression of orthogonalized market participation on the perceived likelihood that the market will increase by more than 20%—as the coefficients associated with the PGS and non-PGS portions have opposite signs. Specifically, the PGS component is negative suggesting it may capture the genetic share of investor views of the riskiness of stock returns, while the non-PGS component is positive suggesting it may better capture investor views of very favorable returns (when excluding risk aversion and the other beliefs from the analysis).

Columns (5) and (10) report the coefficients from regressions in which we include the PGS and non-PGS components of all four measures (risk aversion and the three return belief metrics) simultaneously as regressors. Recognize, however, that because the PGS components are fitted values from the same eight explanatory variables (i.e., the PGSs), variation in the PGS components are highly correlated. Specifically, the absolute value of the correlation between the four predicted (i.e., PGS) components averages 65% versus 15% for the four residual (non-PGS) components.[48] As a result, the PGS components exhibit high levels of collinearity reducing the power of the tests. Importantly, however, the collinearity does not bias the R^2 (or how the R^2 is apportioned between the PGS and non-PGS components).

Results in column (5) of Panel B suggest that the eight genetic endowments account for 32% of the relation between individuals' equity market participation and their risk aversion and beliefs regarding the distribution of equity returns. Similarly, results in column (10) suggest that the eight genetic endowments can explain 20% of the relation between the fraction of assets individuals hold in equity and their risk aversion and beliefs. In sum, genetic endowments associated with cognition, personality, health, and body shape play a substantial role in linking stock market participation to risk aversion and beliefs.[49]

VI.B. The Role of the Eight PGSs in linking Economic Outcomes and Investor Characteristics

Given the 11 investor characteristics are a function of the eight genetic endowments (see Table VI), environment, and other (unknown) genetic endowments, we next estimate how much of the relation between these characteristics and outcomes can be attributed to variation in the characteristic predicted by the eight genetic endowments. Following our previous analysis, we

[48] For example, Panel B in Table III shows that the genetic endowment associated with Neuroticism is positively associated with risk aversion, beliefs regarding the likelihood of at least 20% gain in equity prices, and beliefs regarding the likelihood of at least a 20% decline in equity prices. As a result, a higher Neuroticism PGS will be associated with a simultaneous increase in the PGS components of risk aversion, beliefs regarding the likelihood of at least 20% increase in equity markets, and beliefs regarding the likelihood of at least a 20% decline in equity markets. Note that Table III values are based on regressions of risk aversion or return beliefs, whereas the genetic components used in Table VIII are based on estimates of risk aversion or return beliefs after accounting for variation attributed to the control variables and the 10 genetic principal components. As shown in the Internet Appendix, however, the relations between outcomes and the PGSs (Table III) are nearly identical to the relation between orthogonalized outcomes and the PGSs that are used in Table VIII.

[49] Although the estimates are similar to heritability estimates (e.g., 30% of the variation in risk aversion is heritable), it is important to recognize that our molecular genetics work is addressing a different question (e.g., "how much of the relation between risk aversion and stock market participation can be explained by these eight endowments?" versus "how much of the of the variation in risk aversion is due to genetics?"). As a result, the magnitudes of the coefficients in our molecular genetics study and twin studies cannot be directly compared.

begin by regressing each of the outcome variables (as in Table VIII) and each of the characteristics on the first 10 principal components of the genetics data and the control variables (indicators for HRS waves, age, gender, retired, and married). The residuals from these regressions—denoted orthogonalized outcomes or orthogonalized investor characteristics—reflect variation in each outcome or characteristic that cannot be explained by the control variables or the 10 genetic principal components.

We then regress each of the orthogonalized investor characteristics on the eight PGSs and denote the portion of the orthogonalized characteristic predicted by the eight PGSs (i.e., the fitted value) as the PGS component of the characteristic and the portion explained by everything else (i.e., the residual) as the non-PGS component (the Internet Appendix reports the coefficient estimates from these regressions). As before, for ease of interpretation, we standardize (rescale to unit variance and zero mean) both the PGS and non-PGS components and then regress each of the orthogonalized outcome variables on PGS and non-PGS components of each of the orthogonalized investor characteristic variables. Because the PGS and non-PGS components are mechanically independent, analogous to Equations (2) and (3), the R^2 from these regressions can be directly partitioned into the portion attributed to the eight PGSs (the PGS component) and the portion attributed to everything else (the non-PGS component).

Panel A in Table IX reports pairs of coefficients from the 66 regressions (six outcomes times 11 characteristics).[50] Panel B reports the R^2 from the regression of the orthogonalized outcome variable on the PGS and non-PGS components of each orthogonalized investor characteristic. Panel C reports the portion of the regression R^2 attributed to the PGS-predicted portion of each characteristic. The results demonstrate that a meaningful portion of the relation between each of the 11 investor characteristics and the economic outcomes arises from the portion of the characteristic predicted by the genetic endowments associated with cognition, personality, health, and body shape. For example, as shown in the fifth row of the first two columns in Panel A, a one

[50] Because the PGS component for each of these 11 characteristics are estimated from the same eight PGSs, we cannot include all 11 PGS components simultaneously as regressors (analogous to the fifth and tenth columns in Table VIII), i.e., the matrix is mechanically singular once including more than eight of the 11 PGS components.

standard deviation higher PGS component of trust is associated with 7.2% greater likelihood of stock market participation, while a one standard deviation higher non-PGS trust is associated with an 8.3% greater likelihood of stock market participation. Therefore, as shown in the fifth row of Panel C, 43% of the relation ($0.072^2/(0.072^2+0.083^2)$) between orthogonalized stock market participation and the two components of orthogonalized trust arises from the portion of orthogonalized trust predicted by the eight genetic endowments and 57% of the relation (i.e., 57% of the R^2) arises from the portion of orthogonalized trust explained by everything else.[51]

[Insert Table IX about here]

As shown in the first column of the bottom row in Table IX, averaged across the 11 characteristics, 38% of the ability of the two components of the characteristic (the PGS and non-PGS components) to explain orthogonalized stock market participation arises from the portion of the characteristic predicted by genetic endowments associated with cognition, personality, health, and body shape. The bottom row of Panel C reports averages ranging from 20% to 52% across the six outcome variables. In addition, for eight of the 11 characteristics—income, education, cognition, trust, sociability, early life poverty, BMI, and health—the portion associated with the eight genetic endowments explains, on average, at least 30% of the regression R^2 across the six outcome variables (i.e., the average value in the Panel C row associated with that characteristic is at least 30%). In short, the results suggest that a substantial portion of the heritability in stock market participation, risk aversion, and beliefs arise, at least in part, because genetic endowments associated with cognition, personality, health, and body shape influence each of the 11 investor characteristics.

VII. CONCLUSIONS

Using Health and Retirement Study data, we provide evidence that genetic endowments associated with cognition, personality, health, and body shape predict equity market participation.

[51] Similar to Table VIII, the signs of the coefficients in "PGS" column of Panel A are identical to the signs of the "Non-PGS" column in all cases except orthogonalized beliefs regarding the likelihood of a greater than 20% market return (and for the insignificant coefficient of Height related to the likelihood of a less than 20% market decline).

Moreover, these endowments, established at least 50 years prior, also predict the two factors that traditional economic theory suggests play the central role in determining heterogeneity in equity exposure: risk aversion and beliefs regarding the distribution of equity returns. The relationships we uncover are both intuitive and consistent with our hypotheses. For example, stock market participation is positively related to genetic endowments associated with Educational Attainment, General Cognition, and Height and inversely related to genetic endowments associated with Neuroticism, Depressive Symptoms, Myocardial Infarction, Coronary Disease, and BMI.

We further show that the genetic endowments associated with cognition, personality, health, and body shape continue to predict stock market participation even when controlling for self-reported risk aversion and beliefs. These results suggest that either the endowments capture dimensions of risk aversion and beliefs not captured by self-reported values or the endowments capture individual differences other than risk aversion and beliefs that influence stock market participation decisions such as variation in circumstances.

To better understand the channels linking individuals' genetic endowments to their stock market participation, we also examine 11 investor characteristics shown in previous research to explain stock market participation. We establish, for the first time, that many of these characteristics appear to influence stock market participation because they are associated with both risk aversion and return beliefs. Moreover, the genetic endowments associated with cognition, personality, health, and body shape predict variation in all 11 of these investor characteristics. In some cases, these characteristics appear to be the primary channel linking a genetic endowment to the economic outcomes. For example, the genetic endowment for Height is no longer meaningfully associated with equity market participation once we control for an individual's realized height. In other cases, however, we fail to identify a specific channel linking the genetic endowment to the economic outcome. The genetic endowment for Neuroticism, for instance, continues to predict variation in risk aversion even when controlling for any of the 11 investor characteristics.

Last, we estimate the relative importance of genetic endowments associated with cognition, personality, health, and body shape in linking stock market participation to risk aversion/beliefs and the 11 investor characteristics. We estimate that these genetic endowments can explain 32% of the relation between stock market participation and risk aversion/beliefs. Across the 11 investor characteristics, the eight genetic endowments explain, on average, 38% of the relation between the characteristic and whether an investor participates in equity markets, 20% of the relation between the characteristic and risk aversion, and more than one-third of the relation between the characteristic and beliefs regarding the distribution of equity returns.

In short, the nitrogenous bases in our DNA—for example, whether we have an A or a G at a specific locus—predict our stock market participation, our risk aversion, and our beliefs regarding the distribution of equity returns. Stock market participation heritability arises, at least in part, because molecular genetic markers associated with cognition, personality, health, and body shape predict (1) variation in risk aversion and beliefs, and (2) variation in investor characteristics. Our evidence provides important links between the latent-variable investor heritability literature and the investor characteristics literature and reveals strong evidence of how and why stock market participation, risk aversion, and beliefs regarding the distribution of equity returns are heritable.

We caution that, analogous to evidence linking genetic scores to educational attainment (e.g., Okbay et al., 2016), we do not suggest that there exists an "equity market participation gene" any more than there exists a gene that causes individuals to graduate from college. Rather, we propose that individual genetic endowments predict equity market participation, at least in part, through genetic influences on risk tolerance, perceptions of the distribution of equity returns, and investor characteristics. These influences may be direct or indirect—genetic endowments may directly impact risk aversion or they may interact with environment to impact risk aversion. For instance, a genetic endowment for high Neuroticism may result in lower sociability and, as Hong, Kubik, and Stein (2004) point out, lower sociability may result in individuals being less likely to "learn" about the historically high returns offered by equity markets (i.e., gene by environment interactions).[52]

Given our results, one might naturally ask what are the benefits of understanding *how* genetic endowments impact choices? First and foremost, there exists a need for basic research to better understand the mechanisms and linkages that underlie individual choices. For example, previous research has found that forecasts by professionals are biased (e.g., Gennaioli, Ma, and Shleifer, 2016; Bordalo, Gennaioli, Ma, and Shleifer, 2020). Our results suggest that genetics play a role in these biased forecasts. Future research could explore this issue further.

Beyond this academic enrichment, the potential policy implications are many. As one example, consider the traditional economic model that treats utility parameters for risk aversion as given and assumes rational distributional beliefs. If tastes and beliefs are, at least partially, impacted by inherent genetic endowments—and we have some understanding of how, and which, endowments influence financial decisions—then there may be straightforward pareto improving social architecture choices that are possible. For example, many individuals may greatly prefer a defined benefit approach, or defined contribution plan with target date funds or a robo-adviser, rather than a large slate of choices within a defined contribution plan. Similarly, the benefits of a robust and stable social security program may be understated when one recognizes the benefits available for individuals with predispositions to make poor financial choices (for example, due to errors in return beliefs that are at least in part driven by genetic endowments related to personality). Moreover, a better understanding of the mechanisms that drive what appears to be suboptimal choices is a fruitful avenue of pursuit when developing best approaches to improve social well-being. For instance, if a genetic tendency towards Neuroticism drives ambiguity aversion that leads to suboptimal choices, there may be opportunities to create securities that hedge ambiguities through innovative contract design. Consider, as an analogy, that handedness has a genetic

[52] As shown in Table VII, however, Neuroticism continues to predict stock market participation even when controlling for sociability.

component (e.g., Medland et al., 2009). Knowing this, perhaps a better solution than forcing all left-handed individuals to use their right hand is to develop left-handed tools.

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APPENDIX A – VARIABLE DETAIL AND CONSTRUCTION

Panel A: Economic outcome variables (Source: Combination of RAND HRS fat files and RAND HRS Longitudinal File 2016 (V1))	
Equity participation	Equity participation equals one if the respondent reports holding equities (i) in their pension fund(s), (ii) in IRA/KEOGH accounts, or (iii) directly. (i) Pension fund information comes from the employment and pension section of the interview. Specifically, respondents are asked how much money is in the pension plan now and what percent of this plan is invested in stock? This question is asked of both spouses for households with partners (i.e., the data are at the respondent level). If either spouse reports any of their pension wealth (respondents are asked about multiple pensions if they have more than one pension) is invested in the stock market we code the household (associated with the financial respondent) as participating in equity markets via their pension assets. In 2010, the respondent is limited to a maximum of four pension plans (i.e., eight per household for partnered households). In 2012, HRS changed the structure of the pension section and no longer limited the number of pension funds to four per respondent. We find, however, that very few respondents report more than four pension plans. Respondents who answer they are not sure what fraction is invested in equities, are asked a series of "unfolding" brackets to approximate the amount, e.g., is it less than 40% and more than 20%? In cases where the respondent answer is greater than zero, we code the household as investing in the stock market. (ii) The IRA/KEOGH information comes from the financial respondent's interview regarding household assets and income. Specifically, the financial respondent is asked, "Do you [or your] [husband/wife/partner] currently have any money or assets that are held in an Individual Retirement Account, that is, in an IRA or KEOGH account?" For those households that respond positively, the financial respondent is asked if any of that IRA/KEOGH is invested in stocks or mutual funds, how much is in each account, and what fraction of the IRA/KEOGH is invested in stock. If the household has more than one IRA/KEOGH, the financial respondent is asked about them in order of size up to the three largest IRA/KEOGH accounts. If the financial respondent reports any of the household IRA/KEOGH accounts are at least partially invested in the stock market we code the household as participating in their IRA/KEOGH. (iii) The direct holdings information also arises from the assets and income section of the HRS interview. Specifically, financial respondents are asked "Aside from anything you have already told me about, do you [or your] [husband/wife/partner] have any shares of stock or stock mutual funds?" Respondents who answer yes are classified as participating directly (i.e., in non-retirement accounts) in equity markets following previous work (e.g., Addoum, Korniotis, and Kumar, 2017; Hong, Kubik, and Stein, 2004). In addition, respondents who answer yes to this question are also asked the value of the stock holdings as well as the value other financial assets.

%Equity	We compute the fraction of all (including retirement) wealth invested in equities as the sum of the value of direct stocks holdings, IRA/KEOGHs held in stock (inferred from IRA/KEOGH account values and percent invested in stock), and pension funds held in stock (inferred from the pension fund account values and percent invested in stock) divided by the sum of total financial wealth, IRA/KEOGH account values, and pension fund account values. We winsorize %Equity at the 99% level. We follow RAND (see https://www.rand.org/labor/aging/dataprod.html) and compute non-housing financial wealth as the sum of checking/savings/money market funds, CDs/government savings bonds/Treasury bills, corporate/municipal/government or foreign bonds/bond funds, other savings or assets, less other (non-housing) debt. We compute the fraction of direct financial wealth invested in equities as the value of direct equity holdings (see iii above) divided by non-housing financial wealth.
Risk aversion	In the 2014 and 2016 waves, respondents were asked “Are you generally a person who tries to avoid taking risks or one who is fully prepared to take risks? Please rate yourself from 0 to 10, where 0 means ‘not at all willing to take risks’ and 10 means ‘very willing to take risks.’” We subtract the respondent’s average (over years 2014 and 2016) score to this question from 10 and then rescale the value to zero mean and unit variance (for ease of interpretation).
$P(R_m > 0)$	Respondent response in each HRS wave to the question, “We are interested in how well you think the economy will do in the future. 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?” Note that in 2014, about half of interviewees were instead asked “What do you think is the percent chance that the stock market will be higher in twelve months than it is today?” We find no evidence of a meaningful difference in the two versions of this question.
$P(R_m > 20\%)$	Respondent response in each HRS wave to the question, “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 have gained in value by more than 20 percent compared to what they are worth today?” Note that in 2014, about half of interviewees were instead asked “What do you think is the percent chance that the stock market will be at least 20% higher in twelve months than it is today?”
$P(R_m < -20\%)$	Respondent response in each HRS wave to the question, “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 have fallen in value by more than 20 percent compared to what they are worth today?” Note that in 2014, about half of interviewees were instead asked “What do you think is the percent chance that the stock market will be at least 20% lower in twelve months than it is today?”

	Panel B: HRS computed polygenic scores (Source: HRS Polygenic Scores – Release 2, 2006-2012 Genetic Data, April 2018)
Educational Attainment PGS	Weights from the 2016 Social Science Genetic Association Consortium (SSGAC) based on 293,723 individuals in the discovery sample and 111,349 individuals in the replication sample (see Okbay et al. (2016))
General Cognition PGS	Weights from the 2015 Cohorts for Heart and Aging Research in Genomic Epidemiology (CHARGE) based on 53,949 individuals who took multiple diverse cognition tests (see Davies et al. (2015))
Neuroticism PGS	Weights from the 2016 Social Science Genetic Association Consortium (SSGAC) based on 170,911 individuals (see Okbay et al. (2016) and de Moor et al. (2015))
Depressive Symptoms PGS	Weights from the 2016 Social Science Genetic Association Consortium (SSGAC) based on 180,866 individuals (see Schunkert et al. (2011))
Myocardial Infarction PGS	Weights from the 2015 Coronary ARtery DIsease Genome wide Replication And Meta-analysis (CARDIoGRAM) consortium based on 184,305 individuals (see CARDIoGRAMplusC4D Consortium (2015))
Coronary Disease PGS	Weights from the 2011 Coronary ARtery DIsease Genome wide Replication And Meta-analysis (CARDIoGRAM) consortium based on 86,995 individuals (see Okbay et al. (2016) and de Moor et al. (2015))
BMI PGS	Weights from the 2015 Genetic Investigation of ANthropometric Traits (GIANT) consortium based on samples totaling 322,154 individuals (see Locke et al. (2015))
Height PGS	Weights from the 2014 Genetic Investigation of ANthropometric Traits (GIANT) consortium based on 253,288 individuals in the discovery sample and 80,067 individuals in the replication sample (see Wood et al. (2014))
	Panel C: Investor characteristics used in previous studies (Source: Unless otherwise noted, combination of RAND HRS fat files and RAND HRS Longitudinal File 2016 (V1))
Wealth	We hypothesize a positive relation with equity market participation due to lower direct and indirect participation costs including, for example, "acquiring enough information about risks and returns to determine the household's optimal mix between stocks and riskless assets" (Vissing-Jorgensen, 2002). Given that most individuals greatly underestimate the mean return and overestimate market risk, learning should shift the expected return beliefs right and shrink the market risk estimate (i.e., probabilities associated with extreme returns). Moreover, if relative risk aversion is decreasing, then wealth will be inversely related to risk aversion (see, for instance, Calvet and Sodini, 2014). Thus, wealth may impact participation via direct costs, risk aversion, and beliefs. We measure raw real (CPI-adjusted to 2010 dollars) wealth defined as the total wealth variable (ATOTB) from the RAND HRS Longitudinal File 2016 (V1). These data include RAND imputed wealth observations (see documentation for details). We winsorize raw real wealth at the 1% and 99% level. The minimum raw real winsorized wealth is slightly greater than -$50,000. Therefore we add $50,000 to our real wealth variable (to

	ensure households with negative wealth are not excluded from our data) and take the natural logarithm to mitigate skewness.
Income	We hypothesize a positive relation with equity market participation due to lower direct and indirect participation costs (e.g., Vissing-Jorgensen, 2002). Directly analogous to wealth, higher incomes may be associated with lower direct costs, lower risk aversion, and more optimistic beliefs regarding the distribution of expected returns. We use the total household income (ITOT) from the RAND HRS Longitudinal File 2016 (V1). These data include RAND imputed income observations (see documentation for details). We convert all values to 2010 dollars and winsorize at the 1% and 99% level before taking the natural logarithm.
Education	We hypothesize a positive relation with equity market participation due to better understanding of financial markets and cognitive ability. Education may also impact participation via higher labor income. See Cole, Paulson, and Shastry (2014) for evidence of the positive relation between stock market participation and education. Empirical evidence suggests cognitive ability is inversely related to risk aversion (e.g., Dohmen, Falk, Huffman, and Sunde, 2010). We use years of education as our measure of education.
Cognitive ability	We hypothesize a positive relation with equity market participation due to improved information processing skill, income, wealth, and education. As noted for education (above), evidence suggests cognitive ability is inversely related to risk aversion and greater cognitive ability should shift beliefs regarding the likelihood of the market rising higher and the likelihood of an extreme market return lower. For evidence regarding cognitive ability and market participation see Kezdi and Willis (2003), Benjamin, Brown, Shapiro (2013), Christelis, Jappelli, and Padula (2010), Grinblatt, Keloharju, and Linnainmaa (2011), and Cole, Paulson and Shasty (2014). Following Fisher, Hassan, Faul, Rodgers, and Weir (2017), we use the HRS total cognition measure which ranges from 0-35, and is based on seven different tests. The first two tests are word recall—in the immediate recall tests, respondents are given a list of 10 nouns (based on four possible lists) and asked to immediately recall as many as possible (score 0-10). The second test is delayed recall. After about five minutes of other questions, respondents are asked a second time to recall as many words as possible (score 0-10). The third test is serial 7s—respondents are asked to subtract 7 from 100 and continue to do so for five trials. Score is the number of correct subtractions (score 0-5). The fourth test is backwards counting—respondents are given two chances to count backwards for 10 consecutive numbers starting from both 20 and 86. The recorded score is 2 points if the task is performed correctly on the first try, 1 point if completed correctly on the second try, and zero if not correct on either attempt. The fifth test asks respondent to name the date and day of week—one point for correct day, year, month, and day of week (0-4 points). The sixth test asks respondents to name two objects "What do you usually use to cut paper?" and "What do you call the kind of prickly plant that grows in the

	desert?" Scores are 1 point for each correct answer (0-2 points). The seventh test asks respondents to name the current President and Vice-President. One point for each correct answer (0-2 points). To ensure a larger sample, we use the average cognition score by each respondent over any of the four waves (2010, 2012, 2014, 2016) where the respondent completed the cognition tests. The 2010-2014 cognition scores include values imputed by HRS (See http://hrsonline.isr.umich.edu/modules/meta/xyear/cogimp/desc/COGIMPdd.pdf). The 2016 score is based on raw data and does not include imputed values. (Source: HRS Cognition dataset for 2010-2014, Rand fat file for 2016)
Trust	We hypothesize a positive relation with equity market participation due to the individual's lower subjective probability of being cheated by equity markets (e.g., Guiso, Sapienza, and Zingales, 2008; Giannetti and Wang, 2016). A perceived likelihood of being cheated by markets results in lower expected return and a higher probability of an extreme left tail return (see Balloch, Nicolae, and Philip, 2015) for individuals with lower trust. To measure trust, the Psychosocial and Lifestyle Questionnaire asks respondents to rate their agreement with five statements, where score 1=strongly disagree, 2=somewhat disagree, 3=slightly disagree, 4=slightly agree, 5=somewhat agree, 6=strongly agree. The five statements are: (1) Most people dislike putting themselves out to help other people, (2) Most people will use somewhat unfair means to gain profit or an advantage rather than lose it, (3) No one cares much what happens to you, (4) I think most people would lie in order to get ahead, and (5) I commonly wonder what hidden reasons another person may have for doing something nice for me. Following the guidance in Smith, Ryan, Fisher, Sonnega, and Weir (2017), we compute the average score for individuals who rate at least three of the five statements. The trust metric is included in the Leave-Behind Questionnaires for 2006, 2008, 2010, and 2012. To ensure a larger sample, we use the average trust score by each respondent over any of the four waves (2006, 2008, 2010, 2012) where the respondent completed the trust questions. Because higher values in the raw data indicate lower trust, we compute trust as 7 less the respondent average trust score over all waves in which they participate from 2006-2012. Thus, trust ranges from 1 to 6 with high values indicating greater trust. Note that the psychosocial and lifestyle questionnaire measures "cynical hostility," a term from psychology to describe the "routine lack of trust of other people" (see Berkman, Kawachi, and Glymour, 2014). For consistency with the economics literature, we refer to this dimension as "trust."
Sociability	We hypothesize a positive relation with equity market participation due to the assumptions that the individual is (1) more informed regarding equities via word-of-mouth and observational learning, and (2) derives utility from socializing about investing (e.g., Hong, Kubik, and Stein, 2004; Guiso, Sapienza and Zingales, 2008; Heimer, 2014). As noted above, because most individuals underestimate the mean return and overestimate market risk, learning (via socialization) should shift the expected return beliefs right and shrink the probabilities

	associated with extreme returns. Hong Kubik, and Stein (2004) propose that individuals who are more social may be more "bold" (less risk averse), but find no evidence of a meaningful relation between their measures of sociability and risk tolerance. Some researchers, however, report a negative relation between risk aversion and sociability (e.g., Nicholson, Soane, Fenton-O'Creevy, and Willman, 2005). The HRS Psychosocial and Lifestyle Questionnaire (Leave-Behind Questionnaire) asks respondents three questions: On average, how often do you do each of the following with any of your friends, not counting any who live with you? (1) meet up? (2) speak on the phone? (3) write or email? Respondents answers are (1) three or more times a week, (2) once or twice a week, (3) once or twice a month, (4) every few months, (5) once or twice a year, or (6) less than once a year or never. Following the guidance in Smith, Ryan, Fisher, Sonnega, and Weir (2017), we score sociability as the average score for respondents who respond to at least two of the three questions. Because the raw scores range from 1-6 and higher values indicate less sociability, we subtract the value from 6 so that sociability ranges from 1 to 6 with higher values implying greater sociability. Because Leave-Behind Questionnaires are given to half the respondents in each wave, we use the respondents' average sociability score over waves they participate in from 2006-2016.
Optimism	We hypothesize a positive relation with equity market participation due to higher expected outcomes (e.g., Puri and Robinson, 2007). Empirically, Puri and Robinson find an inverse relation between risk aversion and optimism. Thus, higher optimism may be associated with lower risk aversion, beliefs of a higher likelihood of markets rising, and beliefs of a lower likelihood of extreme left tail returns. Individual optimism measures come from the Psychosocial and Lifestyle Questionnaire. Specifically, respondents are asked to rate their agreement with six statements, where score 1=strongly disagree, 2=somewhat disagree, 3=slightly disagree, 4=slightly agree, 5=somewhat agree, 6=strongly agree. The six statements are: (1) If something can go wrong for me it will, (2) I'm always optimistic about my future, (3) In uncertain times, I usually expect the best, (4) Overall, I expect more good things to happen to me than bad, (5) I hardly ever expect things to go my way, and (6) I rarely count on good things happening to me. Following Smith, Ryan, Fisher, Sonnega, and Weir (2017), we compute the raw optimism score by multiplying items (1), (5), and (6) by -1 and then averaging across all six values for respondents who answer at least four of the statements. We then compute the respondent average raw optimism score by computing the average over waves they participate in between 2006-2016. Because this value can (theoretically) range from -6 to +6, we add seven so optimism is on a scale from 1 to 13 where higher values indicate greater optimism.

Negative early life experience	We hypothesize a negative relation with equity market participation due to increased risk aversion and/or lower expected returns (e.g., Malmendier and Nagel, 2011). The authors also find evidence consistent with the expected returns explanation but point out that such evidence does not preclude the risk aversion channel. We capture whether individuals grew up with negative early life economic experiences by a dummy variable if any of the four following conditions were met: (1) Respondents answer “poor” to the question, “Now think about your family when you were growing up, from birth to age 16. Would you say your family during that time was pretty well off financially, about average, or poor?”, (2) Respondent answers “yes” to the question, “While you were growing up, before age 16, did financial difficulties ever cause you or your family to move to a different place?”, (3) Respondent answers “yes” to the question, “Before age 16, was there a time when you or your family received help from relatives because of financial difficulties?”, and (4) Respondent answers “yes” to the question, “Before age 16, was there a time of several months or more when your father had no job?”
Height	We hypothesize a positive relation with equity market participation due to lower risk aversion. Addoum, Korniotis, and Kumar (2017) propose that the impact of height on risk aversion may also operate via educational attainment, sociability, and positive early life experience. Dohmen, Falk, Huffman, and Sunde (2010) report empirical evidence that height is inversely related to risk aversion. Persico, Postlewaite, and Silverman (2004) find that the positive relation between height and labor income is primarily accounted for by teen (rather than adult) height suggesting that social effects (such as greater self-esteem) drive the height-wage correlation. Previous research (see Deaton and Arora, 2009) also suggests that height is positively associated with greater positive emotions (e.g., enjoyment) and fewer negative emotions (e.g., sadness). As detailed above, such social/optimism effects could manifest in higher expectations for market returns. Following Addoum, Korniotis, and Kumar (2017), we measure relative height (which we denote height) as the respondent’s height in meters less the average height of individuals of the same age and gender in the same wave.

BMI	We hypothesize a negative relation with equity market participation due to the positive relation between BMI and risk aversion. Addoum, Korniotis, and Kumar (2017) propose the relation between BMI, risk aversion, and stock market participation may also operative via educational attainment, sociability, and early life experience. Empirically, there is a positive association between BMI and depression (see meta-analysis by Luppino et al., 2010). Previous research (e.g., Pasco, Williams, Jacka, Brennan, and Berg, 2013) also demonstrates that BMI is positively related to negative affect (e.g., distress, anger, disgust, fear, and shame) which may result in more pessimistic view of future stock returns. Following Addoum, Korniotis, and Kumar (2017), relative BMI (computed in each wave as respondent's weight in kilograms divided by the respondents height in meters squared) is computed as respondent's BMI less the average BMI for individuals of the same age and gender in the same wave.
Health	We hypothesize a positive relation with equity market participation. Rosen and Wu (2004) suggest health may impact portfolio choice due to changes in "the marginal utility of consumption, degree of risk aversion, rate of time preference, and variability of income." Although the authors find a strong relation between health and equity participation, they find little evidence regarding the channel linking portfolio decisions to health. Other work demonstrates, however, that health is strongly inversely related to negative affect (e.g., see Table 2 in Meeks and Murrell, 2001) and that negative health shocks are associated with increased risk aversion (e.g., Decker and Schmitz, 2016). Therefore, we hypothesize that health will be inversely related to risk aversion, positively related to more optimistic beliefs regarding the distribution of equity returns, and (consistent with Rosen and Wu's evidence), positively related to equity market participation. Health from each respondent's response is determined from the question "Would you say your health is: excellent, very good, good, fair, or poor?" Responses are coded on a five-point scale where excellent=5 and poor=1 (such that higher values reflect better health).
	Panel D: Control variables (Source: Combination of RAND HRS longitudinal file (v2), HRS 2014 tracker file, RAND HRS fat files, HRS raw files))
Age indicators	Indicator variables for respondent's age (31 indicators for age 50-80).
HRS wave indicators	Indicator variables for HRS waves (2010, 2012, 2014, and 2016).
Gender indicator	Indicator variable equals one if respondent is male.
Retired indicator	Indicator variable equals one if respondent's labor force status is retired.
Married indicator	Indicator variable equals one if respondent is married.

TABLE I

DESCRIPTIVE STATISTICS AND CORRELATIONS FOR ECONOMIC OUTCOME VARIABLES AND POLYGENIC SCORES (PGS)

Panel A: Descriptive Statistics for Economic Outcome Variables

	N (1)	Mean (2)	Standard Deviation (3)	Minimum (4)	Maximum (5)
Equity participation	13,200	0.594	0.491	0.000	1.000
%Equity	10,108	0.372	0.388	0.000	1.456
Raw risk aversion	13,200	4.126	2.063	0.000	10.000
Risk aversion	13,200	0.000	1.000	-2.000	2.847
$P(R_m > 0)$	13,200	46.942	26.717	0.000	100.000
$P(R_m > 20\%)$	13,200	27.376	22.718	0.000	100.000
$P(R_m < -20\%)$	13,200	30.166	23.288	0.000	100.000

Panel B: Correlations between Economic Outcome Variables

	Equity participation	%Equity	Risk aversion	$P(R_m > 0)$	$P(R_m > 20\%)$	$P(R_m < -20\%)$
Equity participation	1.000					
%Equity	0.630	1.000				
Risk aversion	-0.156	-0.139	1.000			
$P(R_m > 0)$	0.225	0.205	-0.120	1.000		
$P(R_m > 20\%)$	0.022	0.026	-0.006	0.517	1.000	
$P(R_m < -20\%)$	-0.097	-0.088	0.035	-0.241	-0.012	1.000

TABLE I (CONTINUED)

DESCRIPTIVE STATISTICS AND CORRELATIONS FOR ECONOMIC OUTCOME VARIABLES AND POLYGENIC SCORES (PGS)

Panel C: Descriptive Statistics for PGS Variables					
	N (1)	Mean (2)	Standard Deviation (3)	Minimum (4)	Maximum (5)
Educational Attainment PGS	13,200	0.0	1.0	-3.747	3.463
General Cognition PGS	13,200	0.0	1.0	-3.942	3.975
Neuroticism PGS	13,200	0.0	1.0	-3.729	3.475
Depressive Symptoms PGS	13,200	0.0	1.0	-3.363	3.605
Myocardial Infarction PGS	13,200	0.0	1.0	-3.647	3.265
Coronary Artery Disease PGS	13,200	0.0	1.0	-3.718	3.396
BMI PGS	13,200	0.0	1.0	-3.645	4.096
Height PGS	13,200	0.0	1.0	-4.334	2.669

Panel D: Correlations between PGS Variables								
	Educational Attainment	General Cognition	Neuroticism	Depressive Symptoms	Myocardial Infarction	Coronary Artery	BMI	Height
Educational Attainment	1.000							
General Cognition	0.273	1.000						
Neuroticism	-0.063	0.052	1.000					
Depressive Symptoms	-0.091	-0.007	0.547	1.000				
Myocardial Infarction	-0.143	-0.076	0.014	0.047	1.000			
Coronary Artery	-0.116	-0.081	0.041	0.046	0.417	1.000		
BMI	-0.163	-0.060	-0.126	-0.027	0.079	0.027	1.000	
Height	-0.093	-0.089	0.013	-0.040	0.082	-0.004	-0.175	1.000

Notes. This table reports summary statistics and correlations for the economic outcome variables and polygenic scores. The sample period includes HRS waves 2010, 2012, 2014, and 2016. Appendix A provides details for all variables.

TABLE II

DESCRIPTIVE STATISTICS AND CORRELATIONS FOR INVESTOR CHARACTERISTICS

Panel A: Descriptive statistics for investor characteristics

	N	Mean	Standard Deviation	Minimum	Maximum
	(1)	(2)	(3)	(4)	(5)
ln(Wealth)	13,200	12.522	1.354	6.386	15.478
ln(Income)	13,200	10.821	0.977	7.553	13.177
Years of education	13,200	13.847	2.393	0.000	17.000
Cognition	11,611	24.017	3.690	5.750	34.000
Trust	12,096	4.168	0.988	1.000	6.000
Sociability	12,272	3.940	0.920	1.000	6.000
Optimism	12,613	8.062	0.909	3.800	9.622
Grew up poor	13,196	0.400	0.490	0.000	1.000
Height (relative)	13,200	0.011	0.066	-0.362	0.362
BMI (relative)	13,104	-0.341	5.928	-17.343	35.879
Health	13,196	3.388	1.010	1.000	5.000

Panel B: Correlations between investor characteristics

	ln(Wealth)	ln(Income)	Education	Cognition	Trust	Sociability	Optimism	Poor	Height	BMI	Health
ln(Wealth)	1.000										
ln(Income)	0.436	1.000									
Education	0.307	0.406	1.000								
Cognition	0.189	0.336	0.432	1.000							
Trust	0.178	0.120	0.220	0.181	1.000						
Sociability	0.148	0.134	0.228	0.207	0.240	1.000					
Optimism	0.265	0.246	0.252	0.250	0.483	0.229	1.000				
Poor	-0.086	-0.110	-0.158	-0.102	-0.086	-0.044	-0.075	1.000			
Height	0.053	0.096	0.099	0.093	0.016	0.062	0.076	-0.039	1.000		
BMI	-0.157	-0.051	-0.068	-0.030	-0.103	-0.032	-0.114	0.058	-0.051	1.000	
Health	0.266	0.283	0.234	0.262	0.199	0.140	0.356	-0.126	0.045	-0.226	1.000

Notes. This table reports descriptive statistics and correlation coefficients for the 11 investor characteristics used in previous studies. The sample period includes HRS waves 2010, 2012, 2014, and 2016. Appendix A provides details for all variables.

TABLE III

REGRESSION OF EQUITY MARKET PARTICIPATION, RISK AVERSION, AND BELIEFS ON GENETIC ENDOWMENTS ASSOCIATED WITH COGNITION, PERSONALITY, HEALTH, AND BODY SHAPE

	Equity participation (1)	%Equity (2)	Risk aversion (3)	$P(R_m > 0)$ (4)	$P(R_m > 20\%)$ (5)	$P(R_m < -20\%)$ (6)
Panel A: Outcomes on each PGS individually (+control variables and 10 principal components)						
Edu. Attainment PGS	0.071***	0.040***	-0.045***	1.906***	-0.413	-0.829***
Gen. Cognition PGS	0.022***	0.015**	-0.027*	0.627*	-0.546*	-0.724***
Neuroticism PGS	-0.037***	-0.017**	0.064***	-0.945**	0.658**	1.095***
Depressive Symp. PGS	-0.030***	-0.018***	0.021	-0.591*	0.116	0.514*
Myocardial Infarc. PGS	-0.021***	-0.010*	0.032**	-1.270***	-0.399	0.041
Coronary Disease PGS	-0.011*	-0.008	0.042***	-0.023	0.152	-0.122
BMI PGS	-0.034***	-0.019***	0.010	-0.314	0.236	0.207
Height PGS	0.023*	0.002	-0.044*	0.639	-0.469	-0.554
Panel B: Outcomes on all eight PGSs with all PGS included (+control variables and 10 principal components)						
Edu. Attainment PGS	0.060***	0.035***	-0.028*	1.732***	-0.223	-0.579**
Gen. Cognition PGS	0.005	0.006	-0.016	0.227	-0.450	-0.556**
Neuroticism PGS	-0.017**	-0.004	0.064***	-0.527	0.735**	0.957***
Depressive Symp. PGS	-0.013*	-0.011*	-0.012	-0.062	-0.224	0.013
Myocardial Infarc. PGS	-0.012*	-0.004	0.014	-1.374***	-0.612**	0.021
Coronary Disease PGS	0.002	-0.002	0.031*	0.730**	0.337	-0.238
BMI PGS	-0.021***	-0.011**	0.001	0.128	0.220	0.073
Height PGS	0.008	-0.006	-0.030	0.176	-0.387	-0.347
R^2	10.10%	6.23%	4.86%	5.48%	1.29%	3.39%
Number of clusters	5,130	4,322	5,130	5,130	5,130	5,130
Number of obs.	13,200	10,108	13,200	13,200	13,200	13,200

Notes. Panel A reports coefficients on the PGS variables from separate regressions of each of the economic outcome variables on each of the eight PGSs individually, the first 10 principal components of the genetics data, and the control variables (indicator variables for HRS waves, gender, age, married, and retired). Panel B reports coefficients when including all eight PGSs as regressors simultaneously along with the principal components and the control variables. All PGSs are standardized (rescaled to zero mean unit variance). Appendix A provides details for all variables. In all cases, standard errors are clustered at the respondent level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

TABLE IV
THE ABILITY OF PGS TO PREDICT STOCK MARKET PARTICIPATION
WHEN CONTROLLING FOR RISK AVERSION AND BELIEFS

	Equity Participation		%Equity	
	PGS with risk aversion & beliefs	PGS only	PGS with risk aversion & beliefs	PGS only
	(1)	(2)	(3)	(4)
Edu. Attainment PGS	0.060***	0.071***	0.032***	0.040***
Gen. Cognition PGS	0.016**	0.022***	0.011*	0.015**
Neuroticism PGS	-0.028***	-0.037***	-0.011*	-0.017**
Depressive Symp. PGS	-0.026***	-0.030***	-0.016***	-0.018***
Myocardial Infar. PGS	-0.016**	-0.021***	-0.006	-0.010*
Coronary Disease PGS	-0.009	-0.011*	-0.007	-0.008
BMI PGS	-0.032***	-0.034***	-0.018***	-0.019***
Height PGS	0.017	0.023*	-0.003	0.002

Notes. The first and third columns report coefficients associated with each PGS from regressions of the measures of stock market participation on the following independent variables: each PGS, the risk aversion and the three return belief metrics, the first 10 principal components of the genetics data, and the control variables (indicators for HRS waves, age, gender, retired, and married). Each coefficient reported is from a separate regression. For comparison, the second and fourth columns report the coefficients associated with each PGS from the same regressions as in the first and third columns but without the risk aversion and belief metrics (i.e., the values are identical to the first two columns of Panel A in Table III). Standard errors are clustered at the respondent level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

TABLE V

REGRESSION OF ECONOMIC OUTCOMES ON INVESTOR CHARACTERISTICS USED IN PREVIOUS STUDIES

	Equity participation (1)	%Equity (2)	Risk aversion (3)	$P(R_m > 0)$ (4)	$P(R_m > 20\%)$ (5)	$P(R_m < -20\%)$ (6)
Panel A: Outcomes on controls and investor characteristics individually						
ln(Wealth)	0.230***	0.116***	-0.131***	4.701***	0.289	-2.407***
ln(Income)	0.195***	0.093***	-0.152***	4.457***	-0.280	-1.854***
Education	0.144***	0.082***	-0.166***	4.776***	-0.276	-0.970***
Cognition	0.129***	0.070***	-0.139***	4.239***	-0.762**	-0.786***
Trust	0.095***	0.053***	-0.105***	3.866***	0.557**	-1.694***
Sociability	0.077***	0.040***	-0.162***	2.174***	-0.140	-0.571**
Optimism	0.092***	0.049***	-0.216***	3.680***	0.575**	-1.236***
Poor	-0.047***	-0.021***	0.030**	-0.965***	-0.255	0.550**
Height	0.021***	0.010*	-0.056***	0.528*	-0.474*	0.098
BMI	-0.045***	-0.017***	0.054***	-0.521*	0.079	0.384
Health	0.111***	0.046***	-0.171***	3.464***	0.618**	-1.545***
Panel B: Outcomes on controls and all 11 investor characteristics simultaneously						
ln(Wealth)	0.177***	0.087***	-0.016	2.271***	0.329	-1.817***
ln(Income)	0.060***	0.026***	-0.047***	1.123***	-0.490	-0.268
Education	0.038***	0.027***	-0.088***	2.196***	-0.005	0.435
Cognition	0.040***	0.026***	-0.013	1.326***	-1.330***	-0.193
Trust	0.033***	0.021***	0.042**	1.782***	0.602*	-1.363***
Sociability	0.004	0.006	-0.075***	0.116	-0.023	0.094
Optimism	-0.006	0.006	-0.148***	0.885**	0.438	0.087
Poor	-0.014**	-0.001	-0.018	-0.020	-0.226	0.336
Height	-0.002	-0.001	-0.032**	-0.047	-0.269	0.295
BMI	0.000	0.005	0.016	0.672**	0.381	-0.362
Health	0.030***	0.010*	-0.097***	1.455***	0.884***	-0.582*
R^2	32.87%	14.50%	12.25%	10.56%	1.24%	3.67%
Number of clusters	4,033	3,436	4,033	4,033	4,033	4,033
Number of obs.	10,309	8,039	10,309	10,309	10,309	10,309

TABLE V (CONTINUED)
REGRESSION OF ECONOMIC OUTCOMES ON INVESTOR CHARACTERISTICS USED IN PREVIOUS STUDIES

Notes. Panel A reports coefficients on the investor characteristics from separate regressions of the outcome variables (two measures of equity market participation, risk aversion, and three measures of beliefs regarding the distribution of expected returns) on each of the 11 investor characteristics individually and the control variables (indicator variables for HRS waves, gender, age, married, and retired) (i.e., 66 regressions for 11 explanatory variables times six outcomes). Panel B reports coefficients from regressions of the outcome variables on the 11 explanatory variables simultaneously with the control variables. All independent variables are standardized (i.e., rescaled to zero mean, unit variance). Appendix A provides details for all variables. In all cases, standard errors are clustered at the respondent level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

TABLE VI

REGRESSION OF INVESTOR CHARACTERISTICS USED IN PREVIOUS STUDIES ON POLYGENIC SCORES (PGSS) FOR COGNITION, PERSONALITY, HEALTH, AND BODY SHAPE

	ln(Wlth) (1)	ln(Inc.) (2)	Education (3)	Cognition (4)	Trust (5)	Social (6)	Optimism (7)	Poor (8)	Height (9)	BMI (10)	Health (11)
	Panel A: Investor characteristics on individual PGS (+control variables and 10 principal components)										
Edu. Attainment PGS	0.129***	0.115***	0.225***	0.170***	0.137***	0.069***	0.133***	-0.044***	0.046***	-0.062***	0.100***
Gen. Cognition PGS	0.017	0.030**	0.097***	0.098***	0.053***	-0.014	0.014	-0.001	0.003	-0.014	0.036**
Neuroticism PGS	-0.055***	-0.036***	-0.086***	-0.097***	-0.127***	-0.065***	-0.137***	0.054***	0.008	-0.006	-0.068***
Depressive Symp. PGS	-0.049***	-0.034***	-0.049***	-0.055***	-0.088***	-0.061***	-0.109***	0.034**	-0.002	0.006	-0.062***
Myocardial Infarc. PGS	-0.043***	-0.029***	-0.058***	-0.044***	-0.038**	-0.001	-0.046***	0.024	-0.043***	0.032**	-0.066***
Coronary Disease PGS	-0.028**	-0.023**	-0.037***	-0.011	-0.007	-0.017	-0.013	0.015	-0.010	0.008	-0.044***
BMI PGS	-0.074***	-0.042***	-0.055***	-0.053***	-0.069***	-0.008	-0.065***	0.047***	-0.012	0.276***	-0.090***
Height PGS	0.048*	0.054***	0.082***	0.061**	0.017	0.044	0.065**	-0.059**	0.700***	-0.002	0.031
	Panel B: Investor characteristics on all eight PGS (+control variables and 10 principal components)										
Edu. Attainment PGS	0.113***	0.105***	0.203***	0.143***	0.108***	0.064***	0.106***	-0.027	0.016	-0.018	0.070***
Gen. Cognition PGS	-0.015	0.003	0.048***	0.061***	0.023	-0.031*	-0.017	0.013	-0.029*	0.012	0.011
Neuroticism PGS	-0.021	-0.007	-0.043**	-0.063***	-0.086***	-0.030	-0.083***	0.042**	0.023	-0.002	-0.035**
Depressive Symp. PGS	-0.021	-0.014	0.002	-0.004	-0.035*	-0.040**	-0.056***	0.009	0.009	-0.008	-0.031**
Myocardial Infarc. PGS	-0.023	-0.013	-0.034**	-0.032**	-0.026	0.016	-0.031*	0.013	-0.026*	0.007	-0.043***
Coronary Disease PGS	-0.005	-0.006	0.001	0.019	0.018	-0.018	0.014	0.003	0.019	-0.009	-0.014
BMI PGS	-0.051***	-0.020*	-0.011	-0.020	-0.044***	0.002	-0.042***	0.041**	-0.002	0.273***	-0.070***
Height PGS	0.022	0.031	0.034	0.025	-0.013	0.032	0.035	-0.049*	0.701***	0.008	0.005
R^2	14.07%	32.30%	13.33%	15.46%	6.65%	4.30%	7.27%	1.98%	17.61%	8.33%	8.28%
Number of clusters	5,130	5,130	5,130	4,530	4,693	4,761	4,896	5,128	5,130	5,110	5,130
Number of obs.	13,200	13,200	13,200	11,611	12,096	12,272	12,613	13,196	13,200	13,104	13,196

Notes. Panel A reports coefficients on the PGS variables from separate regressions of each of the 11 investor characteristics on each of the eight PGSs individually, the first 10 principal components of the genetics data, and the control variables (indicator variables for HRS waves, gender, age, married, and retired). Panel B reports coefficients when including all eight PGSs as regressors simultaneously along with the principal components and the control variables. Both dependent and independent variables are standardized (rescaled to zero mean, unit variance). Appendix A provides details for all variables. In all cases, standard errors are clustered at the respondent level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

TABLE VII

IDENTIFYING INVESTOR CHARACTERISTIC CHANNELS LINKING POLYGENIC SCORE (PGS) TO ECONOMIC OUTCOMES

Variable:	None (1)	ln(Wlth.) (2)	ln(Inc.) (3)	Educ. (4)	Cog. (5)	Trust (6)	Social (7)	Optim. (8)	Poor (9)	Height (10)	BMI (11)	Health (12)
Panel A: Equity participation on control variables (+10 principal components), individual investor characteristics, and individual PGSs												
Edu. PGS	0.071***	0.042***	0.049***	0.040***	0.047***	0.060***	0.064***	0.058***	0.069***	0.070***	0.069***	0.060***
Cog. PGS	0.022***	0.018***	0.016**	0.008	0.006	0.015**	0.021***	0.020***	0.022***	0.022***	0.021***	0.018***
Neuro. PGS	-0.037***	-0.024***	-0.030***	-0.025***	-0.024***	-0.027***	-0.034***	-0.025***	-0.034***	-0.037***	-0.037***	-0.029***
Depres. PGS	-0.030***	-0.019***	-0.024***	-0.023***	-0.022***	-0.021***	-0.026***	-0.018***	-0.029***	-0.030***	-0.030***	-0.023***
M. Infarc. PGS	-0.021***	-0.012**	-0.016***	-0.013**	-0.014**	-0.014**	-0.018***	-0.016**	-0.020***	-0.020***	-0.021***	-0.014**
Coronary PGS	-0.011*	-0.005	-0.007	-0.006	-0.007	-0.009	-0.010	-0.010	-0.011*	-0.011*	-0.011*	-0.006
BMI PGS	-0.034***	-0.017***	-0.026***	-0.026***	-0.029***	-0.027***	-0.034***	-0.029***	-0.032***	-0.034***	-0.024***	-0.024***
Height PGS	0.023*	0.012	0.013	0.011	0.009	0.015	0.009	0.012	0.020*	0.008	0.023**	0.019*
Panel B: %Equity on control variables (+10 principal components), individual investor characteristics, and individual PGSs												
Edu. PGS	0.040***	0.027***	0.031***	0.023***	0.031***	0.033***	0.035***	0.033***	0.039***	0.040***	0.040***	0.037***
Cog. PGS	0.015**	0.014**	0.013**	0.008	0.007	0.014**	0.016***	0.016***	0.015**	0.015**	0.015**	0.013**
Neuro. PGS	-0.017**	-0.011*	-0.014**	-0.011*	-0.010	-0.012*	-0.016**	-0.012*	-0.016**	-0.017***	-0.017***	-0.014**
Depres. PGS	-0.018***	-0.013**	-0.015***	-0.015***	-0.017***	-0.012**	-0.016***	-0.012**	-0.017***	-0.018***	-0.017***	-0.016***
M. Infarc. PGS	-0.010*	-0.006	-0.008	-0.005	-0.007	-0.005	-0.007	-0.006	-0.009*	-0.009*	-0.010*	-0.007
Coronary PGS	-0.008	-0.005	-0.006	-0.005	-0.010*	-0.007	-0.009	-0.007	-0.008	-0.008	-0.007	-0.006
BMI PGS	-0.019***	-0.011**	-0.015***	-0.014***	-0.017***	-0.015***	-0.018***	-0.015***	-0.018***	-0.019***	-0.015***	-0.015***
Height PGS	0.002	-0.001	-0.001	-0.004	0.005	-0.002	-0.007	-0.006	0.001	-0.007	0.002	0.001
Panel C: Risk Aversion on control variables (+10 principal components), individual investor characteristics, and individual PGSs												
Edu. PGS	-0.045***	-0.028*	-0.028*	-0.008	-0.025	-0.032**	-0.031**	-0.014	-0.043***	-0.042***	-0.041***	-0.028*
Cog. PGS	-0.027*	-0.025	-0.022	-0.011	-0.020	-0.020	-0.023	-0.020	-0.027*	-0.027*	-0.029*	-0.021
Neuro. PGS	0.064***	0.057***	0.059***	0.050***	0.072***	0.054***	0.050***	0.033*	0.063***	0.065***	0.066***	0.053***
Depres. PGS	0.021	0.014	0.016	0.013	0.020	0.015	0.010	-0.005	0.020	0.021	0.022	0.011
M. Infarc. PGS	0.032**	0.027*	0.028*	0.023	0.027*	0.036**	0.029*	0.021	0.032**	0.030**	0.031**	0.022
Coronary PGS	0.042***	0.038***	0.038***	0.036**	0.041***	0.043***	0.038**	0.039***	0.041***	0.041***	0.042***	0.034**
BMI PGS	0.010	0.000	0.004	0.001	0.012	0.004	0.011	-0.003	0.008	0.009	-0.006	-0.005
Height PGS	-0.044*	-0.038	-0.036	-0.030	-0.048*	-0.041	-0.030	-0.026	-0.042	-0.007	-0.045*	-0.039
Panel D: $P(R_m>0)$ on control variables (+10 principal components), individual investor characteristics, and individual PGSs												
Edu. PGS	1.906***	1.331***	1.429***	0.888***	1.129***	1.451***	1.756***	1.379***	1.865***	1.880***	1.868***	1.572***
Cog. PGS	0.627*	0.549*	0.499	0.172	0.175	0.356	0.614*	0.529	0.635*	0.625*	0.621*	0.503
Neuro. PGS	-0.945**	-0.690*	-0.787**	-0.543	-0.614	-0.874**	-0.953**	-0.533	-0.900**	-0.950**	-0.952**	-0.707*
Depres. PGS	-0.591*	-0.363	-0.445	-0.359	-0.372	-0.386	-0.508	-0.195	-0.554*	-0.590*	-0.593*	-0.370
M. Infarc. PGS	-1.270***	-1.072***	-1.143***	-0.997***	-1.118***	-1.073***	-1.254***	-1.092***	-1.250***	-1.244***	-1.227***	-1.037***
Coronary PGS	-0.023	0.108	0.079	0.151	0.158	0.076	0.071	0.078	-0.013	-0.017	0.005	0.130
BMI PGS	-0.314	0.029	-0.133	-0.055	-0.068	-0.167	-0.274	-0.057	-0.267	-0.306	-0.193	-0.003
Height PGS	0.639	0.416	0.405	0.249	0.246	0.463	0.434	0.314	0.584	0.211	0.723	0.528

TABLE VII (CONTINUED)

IDENTIFYING INVESTOR CHARACTERISTIC CHANNELS LINKING POLYGENIC SCORE (PGS) TO ECONOMIC OUTCOMES

Variable:	None (1)	ln(Wlth.) (2)	ln(Inc.) (3)	Educ. (4)	Cog. (5)	Trust (6)	Social (7)	Optim. (8)	Poor (9)	Height (10)	BMI (11)	Health (12)
Panel E: $P(R_m>0.2)$ on control variables (+10 principal components), individual investor characteristics, and individual PGSs												
Edu. PGS	-0.413	-0.452*	-0.378	-0.357	-0.349	-0.465*	-0.375	-0.514*	-0.420	-0.398	-0.436	-0.480*
Cog. PGS	-0.546*	-0.551*	-0.536*	-0.519*	-0.351	-0.621**	-0.592**	-0.638**	-0.552*	-0.545*	-0.569**	-0.569**
Neuro. PGS	0.658**	0.673**	0.646**	0.633**	0.403	0.571*	0.579*	0.670**	0.669**	0.661**	0.667**	0.705**
Depres. PGS	0.116	0.129	0.105	0.101	-0.084	0.081	0.017	0.081	0.120	0.116	0.129	0.161
M. Infarc. PGS	-0.399	-0.390	-0.410	-0.420	-0.551**	-0.383	-0.395	-0.394	-0.392	-0.414	-0.412	-0.352
Coronary PGS	0.152	0.159	0.144	0.140	0.208	0.144	0.125	0.159	0.155	0.149	0.159	0.179
BMI PGS	0.236	0.255	0.221	0.219	0.281	0.224	0.334	0.367	0.245	0.232	0.231	0.296
Height PGS	-0.469	-0.481	-0.450	-0.443	-0.259	-0.395	-0.542	-0.531	-0.477	-0.276	-0.434	-0.485
Panel F: $P(R_m<-0.2)$ on control variables (+10 principal components), individual investor characteristics, and individual PGSs												
Edu. PGS	-0.829***	-0.536**	-0.635**	-0.655**	-0.708**	-0.569**	-0.818**	-0.616**	-0.809***	-0.829***	-0.792***	-0.686***
Cog. PGS	-0.724***	-0.684**	-0.672**	-0.640**	-0.597**	-0.682**	-0.797**	-0.730***	-0.724***	-0.723***	-0.734***	-0.669**
Neuro. PGS	1.095***	0.968***	1.032***	1.022***	1.070***	1.079***	1.165***	1.070***	1.077***	1.095***	1.095***	0.997***
Depres. PGS	0.514*	0.399	0.455*	0.470*	0.510*	0.434	0.540**	0.425	0.497*	0.514*	0.518*	0.427
M. Infarc. PGS	0.041	-0.060	-0.011	-0.012	0.103	-0.090	0.013	-0.024	0.029	0.040	0.004	-0.055
Coronary PGS	-0.122	-0.188	-0.163	-0.156	-0.056	-0.254	-0.213	-0.211	-0.124	-0.122	-0.136	-0.192
BMI PGS	0.207	0.034	0.134	0.157	0.188	0.063	0.282	0.169	0.183	0.207	0.094	0.072
Height PGS	-0.554	-0.442	-0.460	-0.479	-0.370	-0.329	-0.288	-0.232	-0.534	-0.621	-0.628	-0.501

Notes. The first column in Panel A reports coefficients on the PGS variables from separate regressions of stock market participation on each of the eight PGSs individually, the first 10 principal components of the genetics data, and the control variables (indicator variables for HRS waves, gender, age, married, and retired). The remaining columns report the coefficient associated with the PGS (in that row) when adding each of the 11 investor characteristic variables individually to the regression. The remaining panels report analogous coefficients for the fraction of financial wealth held in equity, risk aversion, and the three measures of return beliefs. Independent variables are standardized (rescaled to zero mean, unit variance). Appendix A provides details for all variables. In all cases, standard errors are clustered at the respondent level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

TABLE VIII

THE ROLE OF THE PGSS ASSOCIATED WITH COGNITION, PERSONALITY, HEALTH, AND BODY SHAPE IN LINKING STOCK MARKET PARTICIPATION TO RISK AVERSION AND BELIEFS

	Orthogonalized Equity participation					Orthogonalized %Equity				
	Panel A: Equity market participation on risk aversion and beliefs regarding expected return distribution									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Orthogonalized:										
Risk aversion	-0.054***				-0.045***	-0.040***				-0.035***
P(R_m > 0)		0.090***			0.103***		0.065***			0.071***
P(R_m > 20%)			0.017***		-0.040***			0.014***		-0.022***
P(R_m < -20%)				-0.044***	-0.019***				-0.031***	-0.014***
R^2	1.29%	3.62%	0.12%	0.86%	5.32%	1.13%	2.99%	0.14%	0.69%	4.29%
Panel B: Equity market participation on portion of risk aversion and beliefs related to PGSs and portion orthogonal to PGSs										
Orthogonalized:										
Risk aversion PGS	-0.054***				0.010	-0.030***				0.004
P(R_m > 0) PGS		0.063***			0.087***		0.029***			0.035***
P(R_m > 20%) PGS			-0.035***		-0.051***			-0.028***		-0.034***
P(R_m < -20%) PGS				-0.059***	0.034*				-0.024***	0.018**
Risk aversion non-PGS	-0.050***				-0.042***	-0.038***				-0.033***
P(R_m > 0) non-PGS		0.085***			0.096***		0.063***			0.067***
P(R_m > 20%) non-PGS			0.018***		-0.035***			0.016***		-0.019***
P(R_m < -20%) non-PGS				-0.041***	-0.018***				-0.030***	-0.014***
R^2	2.42%	5.03%	0.68%	2.29%	6.79%	1.64%	3.38%	0.71%	1.03%	4.94%
%R^2 due to PGS	53.98%	35.90%	78.54%	67.12%	31.54%	37.76%	17.73%	76.27%	38.08%	20.28%

Notes. Panel A reports coefficients from regressions of orthogonalized equity market participation on orthogonalized risk-aversion and orthogonalized beliefs where the orthogonalized outcome variables are defined as the residuals from regressions of each of the outcome variables (risk aversion, beliefs regarding the distribution of equity returns, and equity participation measures) on the first 10 principal components of the genetics data and the control variables (indicator variables for HRS waves, gender, age, married, and retired). Panel B reports coefficients from regressions of orthogonalized equity market participation on the portion of orthogonalized risk aversion and orthogonalized beliefs predicted by the eight PGSs and the portion of orthogonalized risk aversion and beliefs independent of the eight PGSs. The bottom row in Panel B reports the portion of the R^2 attributed to variation in the independent variables predicted by the eight PGSs. Standard errors are clustered at the respondent level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

TABLE IX

THE ROLE OF THE EIGHT PGSS IN LINKING INVESTOR CHARACTERISTICS TO ECONOMIC OUTCOMES

	Equity participation		%Equity		Risk aversion		$P(R_m > 0)$		$P(R_m > 20\%)$		$P(R_m < -20\%)$	
Panel A: Outcomes on portion of investor characteristic variable predicted by the PGSs and portion orthogonal to PGSs												
	PGS	Non-PGS	PGS	Non-PGS	PGS	Non-PGS	PGS	Non-PGS	PGS	Non-PGS	PGS	Non-PGS
ln(Wealth)	0.072***	0.207***	0.038***	0.089***	-0.050***	-0.116***	1.819***	4.123***	-0.363	0.283	-0.802***	-2.102***
ln(Income)	0.072***	0.153***	0.039***	0.070***	-0.051***	-0.120***	1.885***	3.401***	-0.411	-0.243	-0.854***	-1.374***
Education	0.070***	0.125***	0.038***	0.070***	-0.055***	-0.150***	1.959***	4.196***	-0.472*	-0.211	-0.953***	-0.682***
Cognition	0.067***	0.110***	0.038***	0.055***	-0.065***	-0.118***	1.893***	3.662***	-0.491*	-0.651**	-1.039***	-0.546**
Trust	0.072***	0.083***	0.038***	0.046***	-0.058***	-0.093***	1.991***	3.513***	-0.414	0.626**	-1.060***	-1.508***
Sociability	0.060***	0.069***	0.027***	0.036***	-0.045***	-0.156***	1.387***	1.960***	-0.299	-0.178	-0.717***	-0.442*
Optimism	0.068***	0.081***	0.034***	0.042***	-0.049***	-0.205***	1.799***	3.394***	-0.334	0.669***	-0.943***	-1.097***
Poor	-0.065***	-0.041***	-0.031***	-0.018***	0.053***	0.026*	-1.541***	-0.822***	0.388	-0.260	0.810***	0.468*
Height	0.022***	0.018***	0.007	0.009*	-0.025*	-0.049***	0.944***	0.443	-0.065	-0.319	-0.331	0.043
BMI	-0.035***	-0.037***	-0.020***	-0.011**	0.011	0.050***	-0.403	-0.378	0.235	0.041	0.229	0.319
Health	0.068***	0.098***	0.035***	0.038***	-0.054***	-0.159***	1.667***	3.117***	-0.346	0.641***	-0.781***	-1.387***

	Equity participation	%Equity	Risk aversion	$P(R_m > 0)$	$P(R_m > 20\%)$	$P(R_m < -20\%)$
Panel B: R^2 from regression of outcome on portion of investor characteristic variable predicted by the PGSs and portion orthogonal to PGSs						
ln(Wealth)	21.52%	6.54%	1.67%	2.99%	0.04%	0.96%
ln(Income)	12.80%	4.46%	1.77%	2.22%	0.04%	0.50%
Education	9.23%	4.47%	2.66%	3.16%	0.05%	0.26%
Cognition	7.42%	3.20%	1.90%	2.46%	0.13%	0.26%
Trust	5.45%	2.46%	1.25%	2.41%	0.11%	0.65%
Sociability	3.77%	1.42%	2.76%	0.85%	0.02%	0.14%
Optimism	5.02%	2.05%	4.64%	2.18%	0.11%	0.40%
Poor	2.65%	0.92%	0.36%	0.45%	0.04%	0.17%
Height	0.36%	0.09%	0.32%	0.16%	0.02%	0.02%
BMI	1.16%	0.36%	0.28%	0.04%	0.01%	0.03%
Health	6.42%	1.89%	2.93%	1.84%	0.10%	0.48%
Panel C: Fraction of regression R^2 explained by portion of investor characteristics variable predicted by the PGSs						
ln(Wealth)	10.95%	15.60%	15.68%	16.29%	62.26%	12.71%
ln(Income)	18.18%	23.94%	15.65%	23.50%	74.08%	27.87%
Education	23.93%	22.81%	11.81%	17.90%	83.40%	66.12%
Cognition	27.39%	32.34%	23.26%	21.08%	36.26%	78.37%
Trust	42.82%	40.29%	27.71%	24.32%	30.48%	33.08%
Sociability	42.84%	35.85%	7.71%	33.39%	73.81%	72.43%
Optimism	41.87%	39.20%	5.51%	21.94%	20.02%	42.48%
Poor	71.08%	74.39%	80.30%	77.86%	69.01%	74.94%
Height	60.40%	39.43%	21.54%	81.93%	3.95%	98.33%
BMI	47.99%	74.68%	4.88%	53.22%	97.05%	34.01%
Health	32.10%	45.24%	10.37%	22.23%	22.59%	24.08%
Average	38.14%	40.34%	20.40%	35.79%	52.08%	51.31%

TABLE IX (CONTINUED)

THE ROLE OF THE EIGHT PGSS IN LINKING INVESTOR CHARACTERISTICS TO ECONOMIC OUTCOMES

Notes. Panel A reports coefficients on investor characteristics variables from separate regressions of each orthogonalized outcome variable on the portion of orthogonalized investor characteristic variable predicted by the eight PGSs and the portion of the orthogonalized investor characteristic variable independent of the eight PGSs, where the orthogonalized outcome variables and orthogonalized investor characteristic variables are defined as the residuals from regressions of each of the outcome variables (equity participation measures, risk aversion, and beliefs regarding the distribution of equity returns) and each of the 11 investor characteristics (e.g., wealth, income, and education) on the first 10 principal components of the genetics data and the control variables (indicator variables for HRS waves, gender, age, married, and retired). Panel B reports the R^2 from each regression and Panel C reports the portion of the R^2 attributed to variation in the investor characteristic variable that can be predicted by the eight PGSs. Appendix A provides details for all variables. Standard errors are clustered at the respondent level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.