Molecular Genetics, Risk Aversion, Return Perceptions, and Stock Market Participation
Q-Group Summary

Imagine a world in which financial advice was tailored to individuals based on known predispositions towards errors that could be avoided and mitigated—with no further intrusion than a saliva swab. Our findings demonstrate an important avenue for future application and research to better understand the under-participation puzzle in equity markets and how apparent suboptimal cross-sectional variability in choice may relate to genetic underpinnings that impact risk aversion, ambiguity aversion, beliefs, and trust in markets. In short, our results suggest there is a financial equivalence to recent personalized medicine advances.

Using a large panel data set that includes financial, psychosocial, demographic, and genetic data for 5,513 individuals across time, we examine the role of genetic endowments—literally variation in the nitrogenous bases that make up the rungs of our DNA—associated with cognition, personality, health, and body type in shaping the financial decisions individuals make. Because the genome is determined at conception and our sample is limited to individuals aged 50 and older, we begin by examining whether these genetic endowments can *predict* heterogeneity in stock market participation. Consistent with our hypothesis, 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 3.8% lower probability of holding any equity more than half a century later.

Additional tests reveal that these genetic endowments impact asset allocation decisions through their impact on both risk aversion and beliefs. A person with a genetic predisposition for neuroticism, for example, tends to exhibit greater self-reported risk aversion and more bearish beliefs regarding the distribution of equity returns (e.g., they believe it is more likely the market will crash in the next year). Self-reported risk aversion and beliefs, however, cannot fully explain the relation between these genetic endowments and stock market participation suggesting that either these genetic endowments (1) capture variation in risk aversion and beliefs beyond self-reported values, or (2) capture variation in circumstances (unrelated to risk aversion and beliefs) that influence stock market participation, or both.

We also examine the ability of the genetic endowments associated with cognition, personality, health, and body shape to predict variation in 11 realized characteristics (e.g., trust, optimism) known to help explain stock market participation. We find strong evidence that the genetic endowments we investigate predict much of the variation in these characteristics that is associated with stock market participation, i.e., important genetic roots underlie the relation between these variables and stock market participation.

Our work yields a better understanding the mechanisms and linkages that underlie individual choices, which leads to a number of important implications for Q-Group members. For example, 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. For example, many individuals may greatly, and *inherently*, prefer a defined benefit approach, or a robo-advised defined contribution plan;

rather than a large slate of choices within a defined contribution plan. Similarly, the benefits of a robust and stable retirement 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 client 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 component. Knowing this, perhaps a better solution than forcing all left-handed individuals to use their right hand is to develop left-handed tools.

Our work also enriches our understanding of behavioral finance and asset pricing. For instance, our results tying genetic endowments associated with neuroticism and depressive symptoms to risk aversion, return beliefs, and market participation, provide support for an asset pricing model that adds anxiety to the utility function (Caplin and Leahy, 2001) that, in turn, can explain the equity premium puzzle. 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, Lo, and Zhang, 2018). Long before financial markets developed, it may have been optimal for species success to have portions of the population with inherent high risk aversion and dour outlooks and to have portions of the population with inherent low risk aversion and overly optimistic outlooks. As a result, many of the behavioral biases documented in the literature likely have genetic roots that are not easily overcome.

Last, given the revolution in molecular genetic research, we are just beginning to recognize how genetic endowments can be used to understand why individuals make the choices they make. In the future, one can imagine new tools to better estimate risk aversion and the tendency for suboptimal financial decisions based on an individual's DNA. Moreover, this information could be used (with all of the associated ethical considerations and caveats) to build customized optimal portfolios. That is, directly analogous to the promise of personalized medicine, low cost genomic sequencing can lead to unique diagnosis and optimized treatments for an individual's finances.

Molecular Genetics, Risk Aversion, Return Perceptions, and Stock Market Participation

August 7, 2019

Richard Sias, Laura T. Starks, and H. J. Turtle*

ABSTRACT

Molecular variation in DNA related to cognition, personality, health, and body shape, established at least half a century prior, predicts an individual's equity market participation, risk aversion, and beliefs regarding the distribution of expected equity returns. Molecular genetic endowments are also strongly associated 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 these genetic endowments can help explain the links between financial choices, risk aversion, beliefs, and other variables known to explain stock market participation.

* Sias is from the Department of Finance, Eller College of Management, University of Arizona, Tucson, Arizona, 85721; (520) 621-3462, sias@eller.arizona.edu. Starks is from the Department of Finance, McCombs School of Business, University of Texas at Austin, Austin, Texas 78712, (512) 471-5899, lstarks@mail.utexas.edu. Turtle is from the Department of Finance and Real Estate, College of Business, Colorado State University, Fort Collins, Colorado, 80523, (970) 491-3596, harry.turtle@colostate.edu. We thank seminar participants at the 2019 Wharton Rodney White Conference on Financial Decisions and Asset Markets, CUNY, Filene, the 2019 Asian Bureau of Finance and Economic Research Meetings, the 2019 Colorado Front Range Seminar, the 2019 Western Finance Association Meetings, and especially Henrik Cronqvist, Stephen Dimmock, Joseph Engelberg, Diego Garcia, Campbell Harvey, David Ikenberry, and Jonathan Hartley for helpful comments.

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

-Lady Gaga

Individuals' investment choices vary from the predictions of traditional utility maximizing theory that prescribe investors hold at least some portion of their wealth in equity markets (e.g., Merton, 1969, 1971) and for most, almost all savings in equity (e.g., Heaton and Lucas, 1997). Further puzzling is that the extensive heterogeneity observed across these choices is related to biological attributes (such as neurochemical activity; see Harlow and Brown, 1990), personality (such as trust; see Guiso, Sapienza, and Zingales, 2008), demographics (such as education; see Cole, Paulson, and Shastry, 2014), and physical characteristics (such as health; see Rosen and Wu, 2004), with little unifying work that is able to satisfactorily explain these findings. A separate vein of research demonstrates the important role of genetic influences as a series of studies estimate "how much" of the heterogeneity in financial decisions for the Swedish population is heritable through the classic twins study approach (e.g., Barnea, Cronqvist, and Siegel, 2010; Cesarini, et al., 2010).

Recent advances in molecular genetics identify specific DNA variations associated with many observable characteristics or traits (known as phenotypes).[1] In this study, we use molecular genetics to better understand *how* and *why* an individual's genome influences their financial choices. In doing so, we link the literature on the heritability of financial decisions with the literature tying those decisions to heterogeneity in investor characteristics. Using a large panel data set from the Health and Retirement Study that includes financial, psychosocial, demographic, and genetic data for 5,513 individuals across time, we examine the role of 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) in shaping heterogeneity in financial decisions.[2]

Because the genome is determined at conception, and our sample is limited to individuals aged 50 to 80, these genetic endowments are established prior to observations of an individual's stock market participation. Thus, we begin by examining whether these eight genetic endowments can *predict*

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

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

heterogeneity in stock market participation more than half a century later. Consistent with our hypothesis, 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.[3] Moreover, the effect sizes are substantial—a one standard deviation higher genetic endowment for Neuroticism predicts a 3.8% lower probability of holding any equity.

The balance of our study focuses on understanding how and why these eight genetic endowments predict stock market participation decisions and linking the heritability literature with the investor characteristics literature. We begin by examining whether the eight genetic endowments predict heterogeneity in risk aversion and return distribution beliefs—the factors driving heterogeneity in equity participation within the traditional utility maximizing framework.[4] The evidence supports the hypothesis that genetic endowments associated with cognition, personality, health, and body shape predict stock market participation, at least in part, because they predict heterogeneity in both risk aversion and beliefs regarding the distribution of equity returns. For example, a higher genetic endowment for Neuroticism predicts both greater risk aversion and more bearish beliefs regarding equity returns including a lower perceived probability that market will rise in the next year and a higher perceived probability the market will crash (a 20% or greater decline) in the next year.

We next test if the relation between these genetic endowments and risk aversion and beliefs can fully explain the relation between the genetic endowments and equity market participation. That is, we test if the relations between these eight genetic endowments, risk aversion, and beliefs are the channels that drive the relation between these genetics endowments and stock market participation. After accounting for heterogeneity in risk aversion and beliefs, most of the eight genetic endowments continue to predict stock market participation choices. For example, after controlling for risk aversion

[3] Several of the genetic scores we examine are meaningfully correlated (e.g., Educational Attainment and General Cognition) and therefore our introductory discussion focuses on relations between outcomes (e.g., equity market participation) and each of the genetic endowments individually. Our empirical work also considers the joint impact of the eight genetic scores on outcomes.

[4] In a traditional framework virtually all investors invest some portion of wealth in risky assets regardless of their risk aversion. In practice, however, many individuals hold no risky assets and as shown in both this and previous studies, this decision is (empirically) related to risk aversion. Moreover, as we detail below, the average individual's view of expected returns are remarkably bearish which could, combined with risk aversion, yield corner solutions with small fixed costs, especially for individuals with small wealth levels (see Vissing-Jorgensen, 2002, Polkovnichenko, 2007, and Kapteyn and Teppa, 2011). Additional potential explanations include, for example, peer effects (e.g., Hong, Kubik, and Stein, 2004) and limited financial capabilities (e.g., Thaler and Benartzi, 2004).

and beliefs, a person with a one standard deviation larger genetic endowment for Depressive Symptoms is 2.5% less likely to hold any equity. We propose that genetic endowments associated with cognition, personality, health, and body shape may continue to predict stock market participation after accounting for heterogeneity in risk aversion and beliefs because they (1) measure heterogeneity in risk aversion or beliefs beyond what is captured by an individual's self-reported values, and (2) 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 investigating the role of genetic endowments associated with cognition, personality, health, and body shape in linking the existing literature tying investor characteristics to stock market participation with the existing heritability literature and thus, understanding the channels that allow these genetic endowments to predict stock market participation. Specifically, we explore the links between the eight genetic endowments and 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. We differentiate these characteristics from risk aversion and beliefs because the 11 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.[5]

We begin this analysis by demonstrating, consistent with previous work, that these 11 investor characteristics explain stock market participation in the expected direction, e.g., equity market participation is positively related to trust and inversely related to growing up poor. We next examine the relation between these 11 characteristics and heterogeneity in risk aversion and 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

[5] The distinction between circumstances and the traditional economic factors (risk aversion and beliefs) can be blurred. For instance, Hong, Kubik, and Stein (2004) suggest that sociability may impact equity market participation as a result of either a non-traditional factor (i.e., an individual garners utility from talking about their stock market participation) or information costs (e.g., an individual may revise their beliefs regarding the distribution of expected equity returns by learning via social relationships about the historically high stock return distribution). Thus, the "information cost" mechanism in this example is that socialization impacts beliefs regarding the distribution of expected equity returns.

associated with heterogeneity in *both* risk aversion and beliefs. For instance, individuals with greater trust tend to exhibit both lower risk aversion and more bullish beliefs, e.g., a lower perceived likelihood of a market crash.

To begin linking the heritability (i.e., twin studies) and investor characteristics literatures, we consider whether the eight genetic endowments predict these 11 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 are more likely to participate in equity markets (Addoum, Korniotis, and Kumar, 2017). Even in less direct cases, however, intuition and previous work suggests the genetic endowments we investigate play a 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 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 we investigate (individually) and the average characteristic is meaningfully related to 5.6 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 genetic endowments associated with Educational Attainment and General Cognition, but negatively predicted by genetic endowments associated with Neuroticism, Depressive Symptoms, Myocardial Infarction, Coronary Artery Disease, and BMI.

We next focus on identifying the specific channels through which each of the eight genetic endowments predicts stock market participation, risk aversion, and beliefs. Our approach is straightforward—we perform a sensitivity analysis to examine if the predictability of each of the eight genetic endowments is subsumed by the inclusion of any of the 11 investor characteristic variables to the regression of stock market participation (or risk aversion/beliefs). 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 height and taller individuals are more likely to hold equities, i.e., realized height is the channel linking the genetic endowment for Height to stock market participation.

In other cases, however, none of the 11 investor characteristics (individually) fully subsumes the predictive ability of the genetic endowment, 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 Educational Attainment continues to predict stock market participation once accounting for realized educational attainment, the genetic endowment for Neuroticism continues to predict participation once accounting for sociability, the genetic endowment for Depressive Symptoms continues to predict participation once accounting for optimism, the genetic endowment for Myocardial Infraction continues to predict participation once accounting for health, and the genetic endowment for BMI continues to predict participation once accounting for actual BMI. In sum, these tests (1) help explain the channels linking these eight genetic endowments to stock market participation, risk aversion, and beliefs and (2) directly link the investor characteristics literature to the heritability literature. For example, stock market participation is heritable, at least in part, because height is heritable and taller individuals are more likely to own equity. Nonetheless, some portion of the ability of these eight genetic endowments to predict economic outcomes remains unexplained suggesting additional, as yet unidentified, phenotypes or combinations of phenotypes link these genetic endowments and stock market participation, risk aversion, and 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 understand how these tests differ from twin studies—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 (Cesarini, et al., 2009). Each approach (twin studies and molecular genetics) has advantages and limitations. For example, molecular genetics is (arguably) poorly suited to estimate phenotypic heritability (due to the "missing heritability" issue discussed in the next section) while twin studies cannot estimate the "genetic portion" of a subject's phenotype or provide evidence regarding why a phenotype is heritable. In contrast, because molecular genetic endowments are for each individual in the sample, one can estimate the component of a phenotype that is attributed to specific genetic endowments such as those associated with cognition, personality, health, and body shape. As a result, molecular genetics allows one to examine both how, and how much of, the *relation* between phenotypes may be attributed to specific endowments. Thus, for example, we can investigate the role of these eight genetic endowments in linking risk aversion and stock market participation. In short, molecular genetics provide a connection between specific genetic underpinnings and financial behavior, in contrast with latent variable approaches available in twin studies.

We begin our final set of tests by demonstrating, consistent with theory, that equity market participation is positively related to risk tolerance and more bullish beliefs. We then 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 these eight genetic endowments in linking risk aversion and beliefs to equity market participation. Our estimates suggest that the genetic endowments associated with cognition, personality, health, and body shape can explain 30% of the relation between a person's risk aversion and return beliefs and their equity market participation.

We similarly estimate the role of these eight genetic endowments in linking the 11 investor characteristics to the economic outcomes (stock market participation, risk aversion, and distributional beliefs). Specifically, we estimate the relation between each of the economic outcomes and the portion of the characteristic (e.g., trust) predicted by the eight genetic endowments versus the portion explained by everything else. We find that much of the relation between economic outcomes and investor characteristics is attributed to the portion of the characteristic predicted by the eight genetic endowments. For instance, the portion of trust predicted by the genetic scores related to cognition, personality, health, and body shape accounts for 41% of the R^2 in a regression of stock market participation on variation in trust predicted by the eight genetic endowments and 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 beliefs have heritable components as all of these economic outcomes are meaningfully related to genetic endowments associated with cognition, personality, health, and body shape. That is, stock market participation heritability arises, at least in part, because cognition, personality, health, and body shape all (1) have genetic components and (2) influence stock market participation, risk aversion, and beliefs. For instance, the genetic endowment associated with Neuroticism is positively related to both risk aversion and the perceived likelihood of a market crash. As a result, an innate genetic predisposition to Neuroticism can help explain why some individuals are more risk averse, why expectations of equity returns differ across individuals, the willingness of an individual to invest in equity markets, and why these outcomes are heritable. Related, these eight genetic endowments link the heritability literature with the investor characteristics literature as all 11 of the investor characteristic variables previously shown to explain stock market participation are predicted by these eight genetic endowments. Thus, stock market participation heritability arises, at least in part, because genetic endowments associated with cognition, personality, health, and body shape influence realized characteristics such as trust, education, optimism, and health and these 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 (1) is related to many of the investor characteristics known to explain stock market participation (e.g., trust) and (2) has a genetic component.[6] Cesarini et al. (2010) and Barnea, Cronqvist, and Siegel (2010) use twin studies to postulate that heritability of portfolio decisions may arise from heritability of risk aversion. Although our evidence is consistent with this causation channel, our tests show that this channel is not unique as genetic endowments associated with cognition, personality, health, and body shape also predict heterogeneity in return beliefs. 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 the genetic endowments we investigate. Further, these equity market return perceptions can help explain why both genetic endowments (e.g., Neuroticism) and investor characteristics (e.g., trust) are related to market participation. That is, what may be an objectively irrational choice (e.g., zero investment in equities), is 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.

Our results also add to the understanding of genetics and finance by examining a different sample and using a different approach than previous work in this area. (We compare our work to related work linking finance and genetics in the next section.) This is important because a trait's heritability is not a biological constant—rather it varies from one population to another and over time. As pointed out by Campbell (2006), this may be especially important in contrast with a relatively homogenous culture

[6] 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 a lower likelihood of believing there is a 0% or 100% chance the market will rise in the next year), and ultimately, retirement wealth. We discuss this paper in the next section.

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. Specifically, we focus on the relations between a broad range of genetic endowments and investor characteristics, risk aversion, expected return distribution beliefs, and equity market participation for an extensive sample of U.S. investors.

Finally, our work adds to our understanding of non-economic (behavioral finance) 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. 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, Lo, and Zhang, 2018). Long before financial markets developed, it may have been optimal for species success to have portions of the population with inherent high risk aversion and dour (bearish) outlooks and to have portions of the population with inherent low risk aversion and overly optimistic outlooks.

One might naturally ask what are the benefits of understanding *how* genetic endowments impact choices? First and foremost, we pursue this topic as basic research—to better understand the mechanisms and linkages that underlie individual choices. Nonetheless, 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 a robo-advised defined contribution plan; 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 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.

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).

I. Background

In an early study investigating biology and risk preferences, Harlow and Brown (1990) establish a relation between risk tolerance and participants' blood enzymes. Developments in twin studies and molecular genetics have allowed for further analyses of the role of biology in an individual's financial decisions. In this section we provide brief overviews of the previous stock market participation (and closely-related) research based on twin studies and molecular genetics.

A. Genetics and Finance – Twin Studies

In the last 50 years, at least 2,700 twin studies infer the role of genetics in more than 17,800 traits (see Polderman et al., 2015) by comparing phenotype differences between monozygotic ("identical") twins who have, essentially, identical DNA, and dizygotic ("fraternal") twins who, the same as any other siblings, 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] Twin studies also suggest that behavioral biases including lack of diversification, excessive trading, the disposition effect, the conjunction fallacy, default bias, and loss aversion are highly heritable.

Although twin study results are usually presented as "nature versus nurture," genetic endowments interact with environmental effects (see Dick, 2011) and therefore, heritability (usually reported as a point estimate) varies across populations and time due to these interactions. Guo (2005) points out, for example, that the twins study estimate 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.

Our work builds on these important heritability studies that estimate "how much" of an economic outcome (such as stock market participation) is "genetic" for the Swedish population. Specifically, as noted in the introduction, our goal 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).

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[7] 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 (2001), 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).

B. 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]

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" or, when referring to multiple SNPs, "snips"). 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

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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 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.

major allele (e.g., adenine, A) while the less common variation is the minor allele.[14] 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 (e.g., Kuhnen and Chiao, 2009), the vast majority of current molecular genetics research focuses on Genome-Wide Association Studies (GWAS).[15,16] 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, 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.[17]

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

[14] Most SNPs are biallelic—meaning there are only two variations (e.g., either A or G in a sequence).

[15] 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 the 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., heart disease) 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.

[16] 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).

[17] 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 ($=\log_{10}(5x10^{-8})$).

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 finance, 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).[18] Although the focus of their study is understanding the relation between an Educational Attainment PGS and wealth inequality, the authors also find that the link between Educational Attainment and income inequality arises, in part, because their Educational Attainment PGS is inversely related to a measure of risk aversion, positively related to stock market participation, 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 fundamentally differs 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 eight genetic endowments can influence individual's 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.

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

C. 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 about 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, 2015). 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.[19]

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.[20]

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[19] 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).

[20] As noted above, the equity market participation literature is very large (Google Scholar reports more than 8,000 results for "stock market participation" in early 2019). The first 11 variables in this list are used in this study and discussed in the next section. We lack sufficient data for most of the other characteristics shown to help explain stock market participation. For evidence regarding the other characteristics mentioned—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).

Empirical evidence also suggests investors engage in a number of presumably irrational behaviors (e.g., loss aversion). As noted in the introduction, for example, theoretical models of species survival posit that innate biological differences may help explain behavioral heterogeneity—including behavior that appears to be irrational for the individual.

II. Data

A. Health Retirement Study

Our data comes from the Health and Retirement Study (HRS) survey data panel of Americans age 50 and older.[21] This age cohort 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.[22] 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 (for which we have 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

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[21] 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.

[22] 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).

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 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.

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. Moreover, any measurement error in our data should only weaken the power of the tests.

B. Molecular Genetic Data

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

$$PGS_i = \sum_{j=1}^{J} W_j G_{i,j} \tag{1}$$

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.[23] In most cases,

[23] 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.

the GWAS weights are computed without HRS data, i.e., the HRS PGSs are out of sample estimates.[24,25] 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. 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 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.

Although the HRS data include PGSs for 29 phenotypes, we focus on eight PGSs based on previous evidence of relations between individual characteristics and equity market participation.[26] Because risk aversion and beliefs are complex characteristics, they are likely related to multiple genetic endowments.[27] As a result, we select two PGSs from each of the four broad genetic classifications we examine (cognition, personality, health, and body shape). First, given evidence that the observed characteristic, cognition, is 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 Shastry, 2014), we include each respondent's genetic

[24] 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).

[25] 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).

[26] For completeness, the Internet Appendix provides our primary tests for the additional 21 PGSs.

[27] 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.

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.[28]

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

We focus on equity market participation, risk aversion, and return beliefs as the economic outcome variables. We generate two measures of stock market participation—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).[29] 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.[30] 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

[28] 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.

[29] 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.

[30] 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.

willing to take risks.'" To compute our risk aversion measure (used for the 2010-2016 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.[31]

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?"[32] 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 …?"[33]

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,

[31] 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.

[32] 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."

[33] 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.

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 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).[34] We also include control variables in our analyses. Specifically, we include indicators for HRS waves, respondent age, gender, retired, and married. Appendix A also provides details regarding construction of the control variables.

E. Descriptive Statistics

We require data for the respondent's genetic endowment, stock market participation, risk aversion, beliefs regarding the distribution of equity market returns, household wealth, household income, age, gender, marital status, and retirement status to be included in the sample. Our final sample consists of 5,513 individuals and 12,555 individual-year observations over four HRS waves (2010, 2012, 2014, and 2016). Table I reports descriptive statistics for the genetic data (PGSs), economic outcome variables, the 11 investor characteristics used in previous studies, and the control variables. Table II reports correlations for the genetic data, economic outcome variables, and the 11 investor characteristics. Note that although some of the variables, such as PGSs, are observed at the individual respondent level and others, such as trust, are based on a respondent's trust estimated over a period of time (see Appendix A), the values in Tables I and II are based on the pooled sample used in our analysis, i.e., there are 5,513 unique Neuroticism PGS observations and the average respondent's equity market participation and beliefs regarding the distribution of expected equity returns is measured 2.3 times implying 12,555 total observations.

[Insert Tables I and II about here]

[34] Although Appendix A provides discussion of these links for each characteristic, several themes are clear. For instance, Malmendier and Nagel (2011) propose that one's early life experience may influence both risk aversion and beliefs, thereby influencing equity market participation. This mechanism can be applied to all the variables we consider, e.g., optimism may be positively associated with both risk tolerance and beliefs regarding the distribution of equity returns, thereby impacting equity market participation.

Panel A in Tables I and II report descriptive statistics and correlations for the genetic data. By construction, the HRS PGS scores are standardized.[35] 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.

Panel B in Table I reveals that 63% of respondents in our sample hold some equities and the average household in our sample has 38% of their financial assets in equities.[36,37] The third row of Panel B reveals substantial variation in self-rated risk aversion with a standard deviation of 2.24 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.[38] 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.[39] Specifically, between 1927 and 2016, rolling 12-month U.S. equity returns averaged 11.86% with a standard deviation of 21.29%. 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

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35 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.

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

37 We find that 31% 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.

38 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) provide a seminal examination of how ambiguity can impact portfolio decisions.

39 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) find that both individual and institutional investors greatly overestimate the likelihood of an extreme one-day stock market crash (that the authors define as greater than 12.82%, i.e., the value of the largest negative one day return associated with the 1929 stock market crash).

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% historically). Individuals, on average, are closer to the historical value for the likelihood of a 20% or greater market gain (mean estimate of 28% versus 34% historically).

Panel B of Table II 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 of Tables I and II report descriptive statistics and correlations, respectively, 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. As shown in Panel D of Table I, our respondents are approximately equally likely to be male or female, the average age is 66, 48% are retired, and 61% are married.

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

A. Do Genetic Endowments for Cognition, Personality, Health, and Body Shape Predict Economic Outcomes?

We begin by examining if the eight molecular genetic endowments help explain variation in the economic outcome variables. Our hypotheses are based on extant literature (see Section II.D and Panel C of Appendix A for details including a brief description of the proposed channels and associated references) that relates heterogeneity in investor characteristics to heterogeneity in equity market participation. 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 will predict greater stock market participation, and consequently may also predict lower risk aversion, a higher perception of the probability of a positive market return, and a lower perception of the 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, and optimism are positively associated with equity market participation, we hypothesize that PGSs associated with Neuroticism and Depressive Symptoms will predict decreased equity market participation, and may also 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. Similarly, given evidence good health is positively associated with equity market participation, we expect the PGSs associated with poor health—Myocardial Infarction and Coronary Artery Disease—will predict decreased market participation, and may also 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 will predict greater market participation, and may also predict 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 the control variables (indicators for HRS waves, age, gender, retired, and married; unreported to conserve space), the 10 HRS genetic principal components (unreported to conserve space), and each of the eight PGSs individually (standard errors are clustered at the respondent level). That is, Panel A reports the results from 48 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, the first cell reveals that a one standard deviation increase in the Educational Attainment PGS is associated with a 6.5% higher likelihood (statistically significant at the 1% level) that an individual holds any equity.[40]

[Insert Table III about here]

[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.

The results in Panel A provide strong support for our hypotheses and reveal that 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, 43 of the 48 reported coefficients have the expected sign and, of those 43 coefficients, 30 differ materially from zero at the 10% level and 27 differ from zero at the 5% level (two-tail tests). None of the five coefficients with an unexpected sign differ materially from zero at the 10% level.

Although the PGSs are correlated (e.g., Panel A of Table II) 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. For example, stock market participation is most strongly related to the Educational Attainment PGS—a one standard deviation greater Educational Attainment PGS predicts a 5.4% greater likelihood of holding any equities. Nonetheless, even when accounting for an individual's genetic predisposition for Educational Attainment, stock market participation is predicted by (at the 10% level or better) the Neuroticism PGS, the Myocardial Infarction PGS, and the BMI PGS. That is, 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.

Panel B (third column) also reveals that risk aversion is most strongly related to the Neuroticism PGS—a one standard deviation greater Neuroticism PGS predicts a 7.5% 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 Neuroticism, risk aversion is also positively related to the Coronary Artery Disease PGS (at the 5% level) and negatively related to the Educational Attainment PGS (at the 10% level).

Heterogeneity in beliefs regarding the distribution of equity returns are related to a number of genetic factors when all eight PGSs are included. Beliefs regarding the likelihood of a market increase are positively related to the Educational Attainment PGS (at the 1% level), inversely related to the Myocardial Infarction PGS (statistically significant the 1% level), and, inconsistent with our priors, positively related to the Coronary Artery Disease PGS (at the 5% level). The results suggest, for example, that a one standard deviation higher Myocardial Infarction PGS predicts an approximately 1.17% lower value for beliefs regarding the likelihood of the market increasing. Given the standard deviation of the dependent variable is 26.48% (see Table I), this represents a 4.4% standard deviation shift (i.e., 1.174/26.483=0.044).

Views regarding the likelihood of an extreme market move (>±20%) are most strongly related to the Neuroticism PGS when simultaneously considering all eight PGSs. Specifically, individuals with a one standard deviation larger Neuroticism PGS predict a 1.01% greater likelihood of market decline in excess of 20% (statistically significant at the 1% level) and a 0.72% greater likelihood of a market increase in excess of 20% (statistically significant at the 5% level) over the next year. Relative to the dependent variable standard deviations reported in Table I, these coefficients suggest that a one standard deviation larger Neuroticism PGS predicts a 4.35% standard deviation higher perceived likelihood of a greater than 20% decline and a 3.20% standard deviation higher perceived likelihood of a greater than 20% increase. Beliefs regarding the likelihood of an extreme market movement are also meaningfully related to the General Cognition PGS in the hypothesized direction.

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 can predict an individual's stock market participation, risk aversion, and beliefs. We next examine if the ability of these genetic endowments to predict self-reported 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.

For ease of comparison, the first and third columns in Table IV report the coefficients associated with each PGS from a regression of each equity market participation measure on the control variables and each PGS individually (i.e., the values from the first two columns of Panel A in Table III). The second and fourth columns report the coefficient associated with each PGS when adding risk aversion and beliefs as regressors. The results reveal 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 endowment's relation with self-reported risk aversion and beliefs—the coefficients remain substantial and statistically significant. For example, a one standard deviation higher Neuroticism PGS is associated with a 3.8% lower likelihood of holding equity. Once accounting for the variation in market participation explained by contemporaneously-measured risk aversion and beliefs, the same Neuroticism shock predicts a 2.9% lower likelihood of holding equity (statistically significant at the 1% level).

[Insert Table IV about here]

There are two non-mutually exclusive reasons 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, these PGSs may capture factors other than risk aversion and beliefs, such as variation in circumstances, that influence stock market participation.

IV. PGSs, Investor Characteristics, and Economic Outcomes

A. Investor Characteristics and Economic Outcomes

We next examine the extent to which these eight genetic endowments can link the investor characteristics and heritability literatures, and investigate the channels through which these endowments predict stock market participation, risk aversion, and beliefs. We begin by evaluating the relations between the economic outcome variables and each of the 11 investor characteristics documented by previous work to help explain equity market participation. Because many of the characteristics are strongly correlated (see Table II Panel C) and our goal is understanding the role of the eight genetic endowments in explaining previously identified relations (rather than determining which of the investor characteristics best explains the outcome variables), we focus on regressions of the outcome variables on the control variables (indicators for HRS waves, gender, age, married, and retired) and each of the investor characteristics individually. In addition, for ease of interpretation and comparison, we standardize (i.e., rescale to zero mean, unit variance) each of the characteristics. The results of 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. The third column reveals that each of the 11 investor characteristics used in previous work to explain equity market participation is also related to risk aversion in the expected direction (10 of the 11 are statistically significant). Specifically, greater wealth, income, education, cognition, trust, sociability, optimism, height, and health are all associated with a lower risk aversion. Conversely, BMI is positively associated with risk aversion.

The last three columns report the relations between the 11 individual characteristics and beliefs regarding the distribution of equity returns. 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 reveal that nine of the 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. 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, all 11 characteristics have the expected sign and 10 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 reveals that a one standard deviation change in the average investor characteristic used in previous work is associated with a 11.1% standard deviation change in risk aversion (recall that risk aversion is also standardized). The average absolute value in the third column of Table III Panel A is 0.037. Thus, on average, the relation between risk aversion and the average genetic endowment in our set (measured more than 50 years prior) is one-third the relation between risk aversion and the average contemporaneously-measured investor characteristic (i.e., 0.037/0.111=0.333). Results are similar across the two equity participation variables (i.e., the average absolute value in the first two columns of Table III are 31% and 30%, 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 endowment range from 26% to 97% of the relation between the beliefs regarding the distribution of expected equity returns and the average of the 11 investor characteristics.

Panel B in Table V examines the relation between the outcome measures and the characteristics when including all 11 investor characteristics in the model simultaneously (and 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 wealth, income, education, sociability, optimism, height, and health. 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 beliefs regarding the distribution of expected stock returns 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, lower health, and early life poverty are all associated with beliefs that a severe (greater than 20%) market decline in the next year is more likely.

B. Do Genetic Endowments for Cognition, Personality, Health, and Body Shape Predict Investor Characteristics?

Having shown the consistency of our work with the previous studies, we now provide novel insights by examining the extent to which genetic endowments associated with cognition, personality, health, and body shape can 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 13.6% 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, General Cognition, and Height PGSs and inversely predicted by the Neuroticism, Depressive Symptoms, Myocardial Infarction, Coronary Artery Disease, and BMI PGSs. In fact, every investor characteristic is meaningfully related to at least three of the eight PGSs and average characteristic variable is meaningfully related to 5.6 of the eight PGSs we investigate.

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 characteristics 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 reveal 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.

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 realizations of 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.

The first column in Panel A of Table VII reports the coefficient associated with each PGS from regressions of stock market participation on the control variables, the 10 genetic principal components, and the PGS (i.e., 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, the first entry reveals that a one standard deviation higher Educational Attainment PGS predicts a 6.5% increase in the likelihood of holding any equity. 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 3.6% increase in the likelihood of holding any stock. 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 reveal 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 substantial reductions in the 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 0.26 correlation between wealth and health reported in Table II), suggesting that wealth may also be a channel linking the Coronary Artery Disease PGS to stock market participation.

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.[41]

[41] 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.

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

V. The Role of the PGS in linking Participation, Risk Aversion, 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 to generate 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 investigate if there are any genetic links connecting these two phenotypes or what specific endowments may link the phenotypes. In contrast, because molecular genetics focuses on genetic risk scores for each individual, we can investigate how phenotypes may 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 control variables and genetic principal components, and then partition the remaining variation into the portion predicted by the eight genetic endowments and variation 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.[42] Because this approach generates predicted and residual components that are, by construction, independent,

[42] By "everything else" we mean, of course, everything else not explained by the control variables. 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.

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.

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, stock market participation 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 begin by regressing the six economic outcome measures (the two equity market participation measures, the risk aversion metric, and the three belief metrics) on the control variables (indicators for HRS waves, age, gender, retired, and married) and the first 10 principal components of the genetics data. The residuals from these regressions—denoted orthogonalized outcomes—reflect variation in each economic outcome that cannot be explained by the control variables or the 10 genetic principal components.

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 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 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 regress orthogonalized risk aversion and orthogonalized beliefs on the eight PGSs (regression estimates are reported in the Internet Appendix). We denote the portion of orthogonalized risk aversion or beliefs predicted by the eight PGSs (i.e., the fitted values) as the PGS component of risk aversion or beliefs and the portion explained by everything else (i.e., the residuals) as the non-

PGS portion of risk aversion or beliefs. We then regress orthogonalized equity market participation on the standardized (for ease of interpretation) PGS and non-PGS components of risk aversion and beliefs. For example, the regression of orthogonalized stock market participation (denoted EQ) on the portion of orthogonalized risk aversion predicted by the eight PGSs (denoted RA_{PGS}) and the portion of orthogonalized risk aversion independent of the eight PGSs (denoted $RA_{Non\text{-}PGS}$) is given by:[43]

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

Because the two components are mechanically uncorrelated, the R^2 can be directly decomposed into PGS and non-PGS components:[44]

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

Panel B of Table VIII reports coefficients from regressions of the two measures of orthogonalized equity market participation on the PGS and non-PGS components of orthogonalized risk aversion and beliefs. The bottom row reports the fraction of the R^2 accounted for by the portion of risk aversion or beliefs predicted by the genetic endowments associated with cognition, personality, health, and body shape, 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 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 4.8% smaller chance of holding equity while a one standard deviation increase in non-PGS risk aversion is associated with a 4.5% lower chance of holding equity. For three of the four variables, the signs of the PGS and non-PGS portions match and across the eight regressions, and the

[43] We exclude the individual i and year t subscripts for notational brevity.

[44] 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 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%.

portion predicted by the eight PGSs, on average, accounts for 39% of the regression R^2 (i.e., the average value in the bottom row across columns 1, 2, 4, 6, 7, and 9 is 39%).

Similar to Panel A, the regression of orthogonalized market participation on the perceived likelihood that the market will increase by more than 20% is unique—as the coefficients associated with the PGS and non-PGS portions have opposite signs (columns 3 and 8). 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.

We next examine the components when including PGS and non-PGS components of all four measures (risk aversion and the three belief metrics) 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.[45] 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 the fifth column of Panel B suggest that these eight genetic endowments account for 30% of the relation between an individual's equity market participation and their risk aversion and beliefs regarding the distribution of equity returns. Similarly, results in the last column suggest that these eight genetic endowments can explain 20% of the relation between the fraction of assets held in equity and 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.

[45] 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 genetic 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. Recognize that Table III values are based on regressions of risk aversion or beliefs, whereas the genetic components used in Table VIII are based on estimates of risk aversion or 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.

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 begin by regressing each of the outcome variables (as in Table VIII) and each of the characteristics on the control variables (indicators for HRS waves, age, gender, retired, and married) and the first 10 principal components of the genetics data. 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).[46] 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 standard deviation higher PGS

[46] 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.

component of trust is associated with 6.8% greater likelihood of stock market participation, while a one standard deviation higher non-PGS trust is associated with an 8.1% greater likelihood of stock market participation. Therefore, as shown in the fifth row of Panel C, 41% of the relation ($0.068^2/(0.068^2+0.081^2)$) 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 59% of the relation (i.e., the 59% of the R^2) arises from the portion of orthogonalized trust explained by everything else.[47]

[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 22% to 56% 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 one-third 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 33%). 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.

VI. Conclusions

Genetic endowments associated with cognition, personality, health, and body shape, established at least 50 years prior, predict equity market participation and the two factors—risk aversion and beliefs regarding the distribution of equity returns—that play the central role in determining equity market participation in traditional economic theory. These relations are 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.

[47] 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.

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. The results suggest that either these endowments capture dimensions of risk aversion and beliefs not captured by self-reported values or these endowments capture factors other than risk aversion and beliefs that influence stock market participation decisions such as variation in circumstances.

To better understand the channels linking the genetic endowments associated with cognition, personality, health, and body shape to stock market participation, we also examine 11 investor characteristics known to explain stock market participation. We show, for the first time, that many of these characteristics appear to influence stock market participation because they are associated with both risk aversion and beliefs regarding the distribution of equity returns. Moreover, 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 controlling 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 eight genetic endowments can explain 30% 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, 22% 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.

REFERENCES

Abraham, Gad, Aki S. Havulinna, Oneil G. Bhalala, Sean G. Byars, Alysha M. De Livera, Laxman Yetukuri, …, and Michael Inouye, 2016, Genomic prediction of coronary heart disease, *European Heart Journal* 37, 3267-3278.

Abraham, Gad, Adam Kowalczyk, Justin Zobel, and Michael Inouye, 2013, Performance and robustness of penalized and unpenalized methods for genetic prediction of complex human disease, *Genetic Epidemiology* 37, 184-195.

Abraham, Gad, and Michael Inouye, 2014, Fast principal component analysis of large-scale genome-wide data, *PLoS ONE* 9, e93766.

Addoum, Jawad M., George Korniotis, and Alok Kumar, 2017, Stature, obesity, and portfolio choice, *Management Science* 63, 3393-3413.

Anagol, Santosh, Vimal Balasubramaniam, and Tarun Ramadorai, 2018, Noise trading and experience effects, working paper, University of Pennsylvania, University of Warwick, and Imperial College London.

Ashraf, Quamrul, and Oded Galor, 2013, The 'Out of Africa' hypothesis, human genetics, and comparative economic development, *American Economic Review* 103, 1-46.

Balloch, Adnan, Anamaria Nicolae, and Dennis Philip, 2015, Stock market literacy, trust, and participation, *Review of Finance* 19, 1925-1963.

Barnea, Amir, Henrik Cronqvist, and Stephan Siegel, 2010, Nature or nurture: What determines investor behavior? *Journal of Financial Economics* 98, 583-604.

Barth, Daniel, Nicholas W. Papageorge, and Kevin Thom, 2018, Genetic endowments and wealth inequality, forthcoming, *Journal of Political Economy*.

Beauchamp, Jonathan P., David Cesarini, Magnus Johannesson, Matthijs J. H. M. van der Loos, Phillipp D. Koellinger, Patrick J. F. Groenen, …, and Nicholas A. Christakis, 2011, Molecular genetics and economics, *Journal of Economic Perspectives* 25, 57-82.

Benartzi, Shlomo, 2001, Excessive extrapolation and the allocation of 401(k) accounts to company stock, *Journal of Finance* 56, 1747-1764.

Benjamin, Daniel J., Sebastian A. Brown, and Jesse M. Shapiro, 2013, Who is "behavioral"? Cognitive ability and anomalous preferences, *Journal of the European Economic Association* 11, 1231-1255.

Benjamin, Daniel J., David Cesarini, Christopher F. Chabris, Edward L. Glaeser, David I. Laibson, Vilmundur Gudnason, …, and Paul Lichtenstein, 2012, The promises and pitfalls of genoeconomics, *Annual Review of Economics* 4, 627-662.

Berkman, Lisa F., Ichiro Kawachi, and M. Maria Glymour, 2014, *Social Epidemiology* (Oxford University Press, New York).

Bernile, Gennaro, Vineet Bhagwat, and P. Raghavendra Rau, 2017, What doesn't kill you will only make you more risk-loving: Early-life disasters and CEO behavior, *Journal of Finance* 70, 167-206.

Bharath, Sreedhar T., and DuckKi Cho, 2016, Ephemeral experiences, long lived impact: Disasters and portfolio choice, Working paper, Arizona State University.

Bonaparte, Yosef, and Alok Kumar, 2013, Political activism, information costs, and stock market participation, *Journal of Financial Economics* 107, 760-786.

Brennan, Thomas J., and Andrew W. Lo, 2011, The origins of behavior, *Quarterly Journal of Finance* 1, 55-108.

Brennan, Thomas J., and Andrew W. Lo, 2012, An evolutionary model of bounded rationality and intelligence, *PLoS ONE* 7, e50310.

Brennan, Thomas J., Andrew W. Lo, and Ruixun Zhang, 2018, Variety is the spice of life: Irrational behavior as adaptation to stochastic environments, *Quarterly Journal of Finance* 8, 1-39.

Bricker, Jesse, and Geng Li, 2017, Credit scores, social capital, and stock market participation, Finance and Economics Discussion Series Working Paper No. 2017-008.

Brown, Jeffrey R., Zoran Ivković, Paul A. Smith, and Scott Weisbenner, 2008, Neighbors matter: Casual community effects and stock market participation, *Journal of Finance* 63, 1509-1531.

Brown, Sue, and Richard Sias, 2019, The fault in our stars: Molecular genetics and technology adoption, Working paper, University of Arizona.

Bush, William S. and Jason H. Moore, 2012, Genome-wide association studies, *PLoS Computational Biology* 8, e1002822.
Calvet, Laurent E. and Paolo Sodini, 2014, Twin picks: Disentangling the determinants of risk-taking in household portfolios, *Journal of Finance* 69, 867-906.
Cameron, Lisa, and Manisha Shah, 2015, Risk-taking behavior in the wake of natural disasters, *Journal of Human Resources* 50, 484-515.
Campbell, John Y., 2006, Household finance, *Journal of Finance* 61, 1533-1604.
Caplin, Andrew, and John Leahy, 2001, Psychological expected utility theory and anticipatory feelings, *Quarterly Journal of Economics* 116, 55-79.
CARDIoGRAMplusC4D Consortium, 2015, A comprehensive 1000 Genomes-based genome-wide association meta-analysis of coronary artery disease, *Nature Genetics* 47, 1121-1130.
Cesarini, David, Christopher T. Dawes, Magnus Johannesson, Paul Lichtenstein, and Björn Wallace, 2009, Genetic variation in preferences for giving and risk taking, *Quarterly Journal of Economics* 124, 809-842.
Cesarini, David, Magnus Johannesson, Patrik K. E. Magnusson, and Björn Wallace, 2012, The behavioral genetics of behavioral anomalies, *Management Science* 58, 21-31.
Cesarini, David, Magnus Johannesson, Paul Lichtenstein, and Björn Wallace, 2009, Heritability of overconfidence, *Journal of the European Economic Association* 7, 617-627.
Cesarini, David, Magnus Johannesson, Paul Lichtenstein, Örjan Sandewall, and Björn Wallace, 2010, Genetic variation in financial decision making, *Journal of Finance* 65, 1725-1754.
Cesarini, David, and Peter M. Visscher, 2016, Genetics and educational attainment, *npj Science of Learning* 2, 1-7.
Choi, James J., David Laibson, Brigitte C. Madrian, and Andrew Metrick, 2009, Reinforcement learning and savings behavior, *Journal of Finance* 64, 2515-2534.
Christelis, Dimitris, Tullio Jappelli, and Mario Padula, 2010, Cognitive abilities and portfolio choice, *European Economic Review* 54, 18-38.
Cohn, A., J. Engelmann, E. Fehr, and M. Marechal, 2015, Evidence for counter-cyclical risk aversion: An experiment with financial professionals, *American Economic Review* 105, 860-885.
Cole, Shawn A., Anna Paulson, and Gauri Kartini Shastry, 2014, Smart money? The effect of education on financial outcomes, *Review of Financial Studies* 27, 2022-2051.
Cotti, Chad, Richard A. Dunn, and Nathan Tefft, 2015, The Dow is killing me: Risky health behaviors and the stock market, *Health Economics* 24, 803-821.
Cronqvist, Henrik, and Stephan Siegel, 2014, The genetics of investment biases, *Journal of Financial Economics* 113, 215-234.
Cronqvist, Henrik, and Stephan Siegel, 2015, The origins of savings behavior, *Journal of Political Economy* 123, 123-169.
Curcuru, Stephanie, John Heaton, Deborah Lucas, and Damien Moore, 2010, Heterogeneity and portfolio choice: Theory and evidence, in *Handbook of Financial Econometrics* (Elsieiver, Amsterdam), 337-382.
Davies, G., N. Armstrong, J. C. Bis, J. Bressler, V. Chouraki, S. Giddaluru, … and I. J. Deary, 2015, Genetic contributions to variation in general cognitive function: A meta-analysis of genome-wide association studies in the CHARGE consortium (N=53,949), *Molecular Psychiatry* 20, 183-192.
de Moor, M. H., S. M. van den Berg, K. J. Verweij, R. F. Krueger, M. Luciano, … and D. I. Boomsma, 2015, Meta-analysis of genome-wide association studies for neuroticism, and the polygenic association with major depressive disorder, 2015, *JAMA Psychiatry* 72, 642-650.
Deaton, Angus and Raksha Arora, 2009, Life at the top: The benefits of height, *Economics and Human Biology* 7, 133-136.
Decker, Simon and Hendrik Schmitz, 2016, Health shocks and risk aversion, *Journal of Health Economics* 50, 156-170.
Dick, Danielle M., 2011, Gene-environment interaction in psychological traits and disorders, *Annual Review of Clinical Psychology* 7, 383-409.
Dimmock, Stephen G., Roy Kouwenberg, Olivia S. Mitchell, and Kim Peijnenburg, 2016, Ambiguity aversion and household portfolio choice puzzles: Empirical evidence, *Journal of Financial Economics* 119, 559-577.
Dohman, Thomas, Armin Falk, David Huffman, and Uwe Sunde, 2010, Are risk aversion and impatience related to cognitive ability? *American Economic Review* 100, 1238-1260.

Dominitz, Jeff, and Charles F. Manski, 2007, Expected equity returns and portfolio choice: Evidence from the health and retirement study, *Journal of the European Economic Association* 5, 369-379.

Dominitz, Jeff, and Charles F. Manski, 2011, Measuring and interpreting expectations of equity returns, *Journal of Applied Econometrics* 26, 352-370.

Dow, James, and Sérgio Ribeiro da Costa Werlang, 1992, Uncertainty aversion, risk aversion, and the optimal choice of portfolio, *Econometrica* 60, 197-204.

Engelberg, Joseph, and Christopher A. Parsons, 2016, Worrying about the stock market: Evidence from hospital admissions, *Journal of Finance* 71, 1227-1250.

Evangelou, Evangelos, and John P.A. Ioannidis, 2013, Meta-analysis methods for genome-wide association studies and beyond, *Nature Reviews Genetics* 14, 379-389.

Evans, Anthony M., and William Revelle, 2008, Survey and behavioral measurements of interpersonal trust, *Journal of Research in Personality* 42, 1585-1593.

Fischhoff, Baruch, and Wändi Bruine De Bruin, 1999, Fifty–fifty=50%? *Journal of Behavioral Decision Making* 12, 149-163.

Fisher, Gwenith G., Halimah Hassan, Jessica D. Faul, Willard L. Rodgers, and David R. Weir, 2017, Health and Retirement Study imputation of cognitive functioning measures: 1992-2014 (Final Release Version), available at http://hrsonline.isr.umich.edu/modules/meta/xyear/cogimp/desc/COGIMPdd.pdf.

Georgarakos, Dimitris, and Giacomo Pasini, 2011, Trust, sociability, and stock market participation, *Review of Finance* 15, 693-725.

Giannetti, Mariassunta, and Tracy Yue Wang, 2016, Corporate scandals and household stock market participation, *Journal of Finance* 71, 2591-2636.

Girirajan, Santhosh, 2017, Missing heritability and where to find it, *Genome Biology* 18, 89.

Goetzmann, William N., Dasol Kim, and Robert J. Shiller, 2017, Crash beliefs from investor surveys, NBER working paper no. 22143.

Goldstein, Benjamin A., Lingyao Yang, Elias Salfati, Themistoclies L. Assimes, 2015, Contemporary considerations for constructing a genetic risk score: An empirical approach, *Genetic Epidemiology* 39, 439-445.

Grinblatt, Mark, Matti Keloharju, and Juhani Linnainmaa, 2011, IQ and stock market participation, *Journal of Finance* 66, 2121-2164.

Guillemette, Michael A., Michael Finke, and John Gilliam, 2012, Risk tolerance questions to best determine client portfolio allocation preferences, *Journal of Financial Planning* 5, 36-44.

Guiso, Luigi, Paola Sapienza, and Luigi Zingales, 2008, Trusting the stock market, *Journal of Finance* 63, 2557-2600.

Guo, Guang, 2005, Twin studies: What can they tell us about nature and nurture? Contexts 4, 43-47.

Harlow, W. V. and Keith C. Brown, 1990, Understanding and assessing financial risk tolerance: A biological perspective, *Financial Analysts Journal* 46, 50-80.

Health and Retirement Study. Produced and distributed by the University of Michigan with funding from the National Institute on Aging (grant number U01AG009740), Ann Arbor, MI.

Heaton, John and Deborah Lucas, 1997, Market frictions, savings behavior, and portfolio choice, *Macroeconomic Dynamics* 1, 76-101.

Heimer, Rawley Z., 2014, Friends do let friends buy stocks actively, *Journal of Economic Behavior and Organization*, 107, 527-540.

Hong, Harrison, Jeffrey D. Kubik, and Jeremy C. Stein, 2004, Social interaction and stock-market participation, *Journal of Finance* 59, 137-163.

Hurd, Michael D., and Susann Rohwedder, 2012, Stock price expectations and stock trading, NBER working paper no. 17973.

Hurd, Michael, Maarten Van Rooij, and Joachim Winter, 2011, Stock market expectations of Dutch households, *Journal of Applied Econometrics* 26, 416-436.

Joseph, Jay, 2013, The use of classical twin method in the social and behavioral sciences: The fallacy continues, *Journal of Mind and Behavior* 34, 1-39.

Kamstra, Mark J., Lisa A. Kramer, and Maurice D. Levi, 2012, A careful re-examination of seasonality in international stock markets: Comment on sentiment and stock returns, *Journal of Banking and Finance* 36, 934-956.

Kapteyn, Arie, and Federica Teppa, 2011, Subjective measures of risk aversion, fixed costs, and portfolio choice, *Journal of Economic Psychology* 32, 564-580.

Katti, Gunnar, Lars Olov Bygren, and Soren Edvinsson, 2002, Cardiovascular and diabetes mortality determined by nutrition during parents' and grandparents' slow growth period, *European Journal of Human Genetics* 10, 682-688.

Kaustia, Markku, and Samuli Knupfer, 2008, Do investors overweight personal experience? Evidence from IPO subscriptions, *Journal of Finance* 63, 2679-2702.

Kaustia, Markku, and Sami Torstila, 2011, Stock market aversion? Political preferences and stock market participation, *Journal of Financial Economics* 100, 98-112.

Keller, Evelyn Fox, and David Harel, 2007, Beyond the gene, *PLoS ONE* 2, e1231.

Kuhnen, Camelia M., and Joan Y. Chiao, 2009, Genetic Determinants of Financial Risk Taking, PLoS ONE 4, 1-4.

Kézdi, Gábor, and Robert J. Willis, 2003, Who becomes a stockholder? Expectations, subjective uncertainty, and asset allocation, unpublished working paper, Central European University and University of Michigan.

Klein, Robert J., Caroline Zeiss, Emily Y. Chew, Jen-Yue Tsai, Richard S. Sackler, Chad Haynes, …, and Josephine Hoh, 2005, Complement factor H polymorphism in age-related macular degeneration, *Science* 308, 385-389.

Knupfer, Samuli, Elias Rantapuska, and Matti Sarvimaki, 2017, Formative experiences and portfolio choices: Evidence from the Finnish great depression, *Journal of Finance* 72, 133-166.

Lee, Boram, Leonard Rosenthal, Chris Veld, and Yulia Veld-Merkoulova, 2015, Stock market expectations and risk aversion of individual investors, *International Review of Financial Analysis* 40, 122-131.

Lillard, Lee, and Robert Willis, 2001, Cognition and wealth: The importance of probabilistic thinking, unpublished working paper, University of Michigan.

Locke, A. E., B. Kahali, S. I. Berndt, A. E. Justice, T. H. Pers, F. R. Day, … and D. C. Croteau-chonka, 2015, Genetic studies of body mass index yield new insights for obesity biology, *Nature* 518, 197-206.

Luppino, Floriana S., Leonore M. de Wit, Paul F. Bouvy, Theo Stijnen, Pim Cuijpers, Brenda W. J. H. Penninx, and Frans G. Zitman, 2010, Overweight, obesity, and depression—A systematic review and meta-analysis of longitudinal studies, *Archives of General Psychiatry* 67, 220-229.

Malmendier, Ulrike, Geoffrey Tate, and Jon Yan, 2011, Overconfidence and early life experiences: The effect of managerial traits on corporate financial policies, *Journal of Finance* 66, 1687-1733.

Malmendier, Ulrike, and Stefan Nagel, 2011, Depression babies: Do macroeconomic experiences affect risk taking? *Quarterly Journal of Economics* 126, 373-416.

Malmendier, Ulrike, and Stefan Nagel, 2016, Learning from inflation experiences, *Quarterly Journal of Economics* 131, 53-87.

Martin, Alicia R., Christopher R. Gignoux, Raymond K. Walters, Genevieve L. Wojcik, Benjamin M. Neale, Simon Gravel, …, and Eimear E. Kenny, 2017, Human demographic history impacts genetic risk prediction across diverse populations, *The American Journal of Human Genetics* 100, 635-649.

Medland, Sarah E., David L, Duffy, Margaret J. Wright, Gina M. Geffen, David A. Hay, Florence Levy,…, and Dorret Boomsma, 2009, Genetic influences on handedness: Data from 25,732 Australian and Dutch twin families, *Neuropsychologia* 47, 330-337.

McInerney, Melissa, Jennifer M. Mellor, and Lauren Hersch Nicholas, 2013, Recession depression: Mental health effects of the 2008 stock market crash, *Journal of Health Economics* 32, 1090-1104.

Meeks, Suzanne and Stanley A. Murrell, 2001, Contribution of education to health and life satisfaction in older adults mediated by negative affect, *Journal of Aging and Health* 13, 92-119.

Merton, Robert C., 1969, Lifetime portfolio selection under uncertainty: The continuous-time case, *Review of Economics and Statistics* 51, 247-257.

Merton, Robert C., 1971, Optimum consumption and portfolio rules in a continuous-time model, *Journal of Economic Theory* 3, 373-413.

Nicholson, Nigel, Emma Soane, Mark Fenton-O'Creevy, and Paul Willman, 2005, Personality and domain-specific risk taking, *Journal of Risk Research* 8, 157-176.

Obeidat, Ma'en, Louise V. Wain, Nick Shrine, Noor Kalsheker, Maria Soler Artigas, Emmanouela Repapi, …, and Veronique Vitart, 2011, A comprehensive evaluation of potential lung function associated genes in the SpiroMeta general population sample, *PLoS ONE* 6, e19382.

Okbay, Aysu, Jonathan P. Beauchamp, Mark Alan Fontana, James J. Lee, and Tune H. Pers, 2016, Genome-wide association study identifies 74 loci associated with educational attainment, *Nature* 533, 539-542.

Pasco, Julie A, Lana J. Williams, Felice N. Jacka, Sharon L. Brennan, and Michael Berk, 2013, Obesity and the relationship with positive and negative affect, *Australian and New Zealand Journal of Psychiatry* 45, 477-482.

Persico, Nicola, Andrew Postelwaite, and Dan Silverman, 2004, The effect of adolescent experience on labor market outcomes: The case of height, *Journal of Political Economy* 112, 1019-1053.

Polderman, Tinca J.C., Beben Benyamin, Christiaan A de Leeuw, Patrick F Sullivan, Arjen van Bochoven, Peter M Visscher, …, and Danielle Posthuma, 2015, Meta-analysis of the heritability of human traits based on fifty years of twin studies, *Nature Genetics* 47, 702-709.

Polkovnichenko, Valery, 2007, Life-cycle portfolio choice with additive habit formation preferences and uninsurable labor income risk, *Review of Financial Studies* 20, 83-124.

Puri, Manju, and David T. Robinson, 2007, Optimism and economic choice, *Journal of Financial Economics* 86, 71-99.

Rosen, Harvey S., and Stephen Wu, 2004, Portfolio choice and health status, *Journal of Financial Economics* 72, 457-484.

Sacerdote, Bruce, 2011, Nature and nurture effects on children's outcomes: What have we learned from studies of twins and adoptees? Chapter 5, J. Benhabib, M. Jackson and A. Bisin (Eds.), Handbook of Social Economics, Amsterdam, North Holland.

Schunkert, H., I. R. Konig, S. Kathiresan, M. P. Reilly, T. L. Assimes, H. Holm, … and D. Absher, 2011, Large scale association analysis identifies 13 new susceptibility loci for coronary artery disease, *Nature Genetics* 43, 333-338.

Shin, Su Hyun, Dean R. Lillard, and Jay Bhattacharya, 2018, Understanding the correlation between Alzheimer's disease polygenic risk, wealth, and the composition of wealth holdings, working paper, University of Alabama, Ohio State University, DIW-Berlin, NBER, and Stanford University.

Simonson, Matthew A., Amanda G. Wills, Matthew C. Keller, and Matthew B. McQueen, 2011, Recent methods for polygenic analysis of genome-wide data implicate an important effect of common variants on cardiovascular disease risk, *BMC Medical Genetics* 12, 146.

Smith, Jacqui, Lindsay Ryan, Gwenith G. Fisher, Amanda Sonnega, and David Weir, 2017, Psychosocial and lifestyle questionnaire 2006-2016, Documentation Report, Core Section LB, available at: https://hrs.isr.umich.edu/publications/biblio/9066.

Stoolmiller, Michael, 1999, Implications of the restricted range of family environments for estimates of heritability and nonshared environment in behavior-genetic adoption studies, *Psychological Bulletin* 115, 392-409.

Turkheimer, Eric, 2000, Three laws of behavior genetics and what they mean, *Current Directions in Psychological Science* 5, 160-164.

Vineis, Paolo, and Neil E. Pearce, 2011, Genome-wide association studies may be misinterpreted: Genes versus heritability, *Carcinogenesis* 32, 1295-1298.

Visscher, Peter M., Naomi R. Wray, Qian Zhang, Pamela Sklar, Mark I. McCarthy, Matthew A. Brown, ..., and Jian Yang, 2017, 10 years of GWAS discovery: Biology, function, and translation, *The American Journal of Human Genetics* 101, 5-22.

Vissing-Jorgensen, Annette, 2002, Towards an explanation of household portfolio choice heterogeneity: Nonfinanical income and participation cost structures, NBER working paper no. 8884.

Ware, Erin B., Lauren L. Schmitz, Jessica Faul, Arianna Gard, Colter Mitchell, Jennifer A. Smith, … Sharon L.R. Kardia, 2017, Heterogeneity in polygenic scores for common human traits, *bioRxiv*, 106062.

Ware, Erin, Lauren Schmitz, Arianna Gard, and Jessica Faul, 2018, HRS documentation report: HRS polygenic scores – Release 2, Survey Research Center, University of Michigan.

Winerman, Lea, 2004, A second look at twin studies, *Monitor on Psychology* 35, 46.

Wood, A. R., T. Esko, J. Yang, S. Vedantam, T. H. Pers, S. Gustafsson, … and N. Amin, 2014, Defining the role of common variation in the genomic and biological architecture of adult human height, *Nature Genetics* 46, 1173-1186.

Yogo, Motohiro, 2016, Portfolio choice in retirement: Health risk and the demand for annuities, housing and risky assets, *Journal of Monetary Economics* 80, 2016.

Zhang, Ruixun, Brennan, Thomas J., and Andrew W. Lo, 2014a, Group selection as behavioral adaptation to systematic risk, *PLoS ONE* 9, e110848.

Zhang, Ruixun, Brennan, Thomas J., and Andrew W. Lo, 2014b, The origins of risk aversion, *Proceedings of the National Academy of Sciences* 111, 17777-17782.

Zuk, Or, Eliana Hechter, Shamil R. Sunyaev, and Eric S. Lander, 2012, The mystery of missing heritability: Genetic interactions create phantom heritability, *Proceedings of the National Academy of Sciences* 109, 1193-1198.

Appendix A – Variable Detail and Construction

Panel A: 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 Symp. PGS	Weights from the 2016 Social Science Genetic Association Consortium (SSGAC) based on 180,866 individuals (see Schunker et al. (2011))
Myocardial Infarc. 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 B: Economic outcome variables (Source: Combination of RAND HRS fat files and HRS raw data files)	
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?”
$P(R_m > 20\%)$	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?”
$P(R_m < -20\%)$	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?”
Equity participation	Equity participation equals one if the respondent reports holding equities in (i) their pension fund(s), (ii) 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.
Panel C: Investor characteristics used in previous studies (Source: Unless otherwise noted, combination of RAND HRS longitudinal file (v2), HRS 2014 tracker file, RAND HRS fat files, HRS raw files)	
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 sum of financial wealth (using the RAND financial wealth definition detailed above), net (loan-adjusted) value of homes, net (loan-adjusted) value of other real estate, value of automobiles, value of business, and IRA/KEOGH value. We winsorize raw real wealth at the 1% and 99% level. The minimum raw real winsorized wealth is slightly greater than -$66,000. Therefore we add $66,000 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 RAND definition of total household income which is the sum of household labor earnings (wages, professional fees, bonus, income from second job), self-employment income, income from investments (real estate, business, stocks, bonds, checking/savings, CDs, other income), income from pensions, social security income, unemployment/workers compensation income, governmental transfers (welfare, veteran income, food stamps), and any other income. 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). As noted above, given the typical individual underestimates the mean return and overestimates market risk, learning (associated with education) should shift the expected return beliefs right and shrink the probabilities associated with extreme returns. 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, HRS raw cognition data for 2016)
Trust	We hypothesize a positive relation with equity market participation due to the individuals' 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 finance 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 more social individuals may be more "bold" (less risk averse), but find no evidence of a meaningful relation between their measures of sociability and risk tolerance. Evidence outside of finance, however, reports 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 trust is a scale from 1 to 13 where higher values indicate greater trust.
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 at time of interview (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 at time of interview.

Table I
Descriptive Statistics

This table reports summary statistics for the Polygenic scores (Panel A), the economic outcome variables (Panel B), 11 investor characteristics used in previous studies (Panel C), and control variables (Panel D). The sample period includes HRS waves 2010, 2012, 2014, and 2016. Appendix A provides details for all variables.

	N	Mean	Standard Deviation	Minimum	Maximum
Panel A: Polygenic score (PGS) variables					
Educational Attainment PGS	12,555	0.0	1.0	-3.744	3.456
General Cognition PGS	12,555	0.0	1.0	-3.921	3.954
Neuroticism PGS	12,555	0.0	1.0	-3.743	3.483
Depressive Symptoms PGS	12,555	0.0	1.0	-3.361	3.606
Myocardial Infarction PGS	12,555	0.0	1.0	-3.647	3.208
Coronary Artery Disease PGS	12,555	0.0	1.0	-3.714	3.397
BMI PGS	12,555	0.0	1.0	-3.649	4.094
Height PGS	12,555	0.0	1.0	-4.344	2.668
Panel B: Economic outcome variables					
Equity participation	12,555	0.626	0.484	0.0	1.0
%Equity	10,142	0.381	0.385	0.0	1.488
Raw risk aversion	12,555	4.085	2.239	0.0	10.0
Risk aversion	12,555	0.0	1.0	-1.825	2.642
$P(R_m > 0)$	12,555	47.390	26.483	0.0	100.0
$P(R_m > 20\%)$	12,555	27.633	22.648	0.0	100.0
$P(R_m < -20\%)$	12,555	30.234	23.197	0.0	100.0
Panel C: Investor characteristics used in previous studies					
ln(Wealth)	12,555	12.511	1.187	8.006	15.354
ln(Income)	12,555	10.793	1.245	5.912	13.935
Years education	12,555	13.885	2.381	0.0	17.0
Cognition	11,061	24.125	3.612	7.667	34.0
Trust	11,554	4.181	0.988	1.0	6.0
Sociability	11,507	3.971	0.946	1.0	6.0
Optimism	11,862	8.072	0.923	4.000	9.850
Grew up poor	12,552	0.400	0.490	0.0	1.0
Height	12,555	0.011	0.067	-0.369	0.364
BMI	12,468	-0.174	5.952	-17.168	34.866
Health	12,553	3.397	1.006	1.0	5.0
Panel D: Control variables					
Male	12,555	0.489	0.500	0.0	1.0
Age	12,555	66.314	8.228	50.0	80.0
Retired	12,555	0.478	0.500	0.0	1.0
Married	12,555	0.612	0.487	0.0	1.0

Table II
Correlations

This table reports correlation coefficients for the Polygenic scores (Panel A), the economic outcome variables (Panel B), and 11 investor characteristics used in previous studies (Panel C). The sample period includes HRS waves 2010, 2012, 2014, and 2016. Appendix A provides details for all variables.

Panel A: Polygenic score (PGS) variables

	Edu. Attain.	Gen. Cognition	Neuroticism	Depressive	Myocardial	Coronary	BMI	Height
Edu. Attain.	1.000							
Gen. Cognition	0.270	1.000						
Neuroticism	-0.066	0.055	1.000					
Depressive	-0.092	-0.006	0.549	1.000				
Myocardial	-0.145	-0.079	0.015	0.048	1.000			
Coronary	-0.116	-0.087	0.043	0.045	0.416	1.000		
BMI	-0.162	-0.061	-0.127	-0.026	0.087	0.024	1.000	
Height	-0.093	-0.089	0.008	-0.045	0.078	-0.006	-0.172	1.000

Panel B: 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	0.623	1.000				
Risk aversion	-0.135	-0.117	1.000			
$P(R_m > 0)$	0.222	0.202	-0.115	1.000		
$P(R_m > 20\%)$	0.028	0.030	-0.011	0.507	1.000	
$P(R_m < -20\%)$	-0.100	-0.087	0.043	-0.241	-0.007	1.000

Panel C: Investor characteristics used in previous studies

	ln(Wealth)	ln(Income)	Education	Cognition	Trust	Sociability	Optimism	Poor	Height	BMI	Health
ln(Wealth)	1.000										
ln(Income)	0.370	1.000									
Education	0.322	0.306	1.000								
Cognition	0.202	0.272	0.429	1.000							
Trust	0.188	0.099	0.223	0.188	1.000						
Sociability	0.154	0.104	0.216	0.216	0.246	1.000					
Optimism	0.266	0.184	0.244	0.239	0.491	0.231	1.000				
Poor	-0.089	-0.091	-0.158	-0.097	-0.079	-0.045	-0.063	1.000			
Height	0.059	0.079	0.100	0.090	0.019	0.065	0.068	-0.039	1.000		
BMI	-0.174	-0.057	-0.079	-0.032	-0.098	-0.025	-0.118	0.051	-0.061	1.000	
Health	0.255	0.225	0.234	0.258	0.203	0.139	0.351	-0.124	0.045	-0.241	1.000

Table III
Regression of Equity Market Participation, Risk Aversion, and Beliefs on Genetic Endowments associated with Cognition, Personality, Health, and Body Shape

We regress each of the outcome variables on the control variables (indicators for HRS waves, age, gender, retired, and married), the first 10 principal components of the genetics data, and each of the eight genetic PGSs individually and report results in Panel A. Panel B reports regression coefficients when including all eight PGSs as regressors simultaneously (and the control variables and 10 principal components). 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.

	Equity participation	%Equity	Risk aversion	$P(R_m > 0)$	$P(R_m > 20\%)$	$P(R_m < -20\%)$
	Panel A: Outcomes on individual PGSs (+control variables and 10 principal components)					
Edu. Attainment PGS	0.065***	0.039***	-0.044***	1.816***	-0.452*	-0.735***
Gen. Cognition PGS	0.022***	0.017***	-0.025	0.707**	-0.597**	-0.877***
Neuroticism PGS	-0.038***	-0.017***	0.079***	-0.958***	0.743**	1.166***
Depressive Symp. PGS	-0.029***	-0.020***	0.031**	-0.461	0.286	0.618**
Myocardial Infarc. PGS	-0.021***	-0.009*	0.021	-1.095***	-0.195	-0.058
Coronary Disease PGS	-0.011*	-0.007	0.043***	0.012	0.228	-0.163
BMI PGS	-0.033***	-0.020***	-0.001	-0.373	0.217	0.337
Height PGS	0.026**	0.000	-0.051**	0.776	-0.322	-0.455
	Panel B: Outcomes on all eight PGSs (+control variables and 10 principal components)					
Edu. Attainment PGS	0.054***	0.033***	-0.027*	1.614***	-0.234	-0.423
Gen. Cognition PGS	0.007	0.009	-0.014	0.322	-0.497*	-0.733***
Neuroticism PGS	-0.020**	-0.002	0.075***	-0.659	0.724**	1.009***
Depressive Symp. PGS	-0.012	-0.014**	-0.006	0.115	-0.057	0.114
Myocardial Infarc. PGS	-0.012*	-0.003	-0.001	-1.174***	-0.411	-0.098
Coronary Disease PGS	0.002	-0.002	0.039**	0.687**	0.325	-0.239
BMI PGS	-0.021***	-0.012**	-0.009	0.042	0.175	0.228
Height PGS	0.011	-0.008	-0.038	0.354	-0.196	-0.250
R^2	10.16%	6.09%	4.15%	5.15%	1.29%	3.32%
Number of clusters	5,513	4,774	5,513	5,513	5,513	5,513
Number of obs.	12,555	10,142	12,555	12,555	12,555	12,555

Table IV
The Ability of PGSs associated with Cognition, Personality, Health, and Body Shape to Predict Stock Market Participation when controlling for Risk Aversion and Beliefs

The first and third columns report regressions of the two measures of stock market participation on the control variables (indicators for HRS waves, age, gender, retired, and married), the first 10 principal components of the genetics data, and each PGS (i.e., the values are identical to the first two columns of Panel A in Table III). The second and fourth columns report the coefficients associated with each PGS when adding risk aversion and the three belief metrics as independent variables to each regression. Standard errors are clustered at the respondent level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	Equity Participation		%Equity	
	PGS only	PGS with risk aversion & beliefs	PGS only	PGS with risk aversion & beliefs
Edu. Attainment PGS	0.065***	0.055***	0.039***	0.032***
Gen. Cognition PGS	0.022***	0.017***	0.017***	0.014**
Neuroticism PGS	-0.038***	-0.029***	-0.017***	-0.011*
Depressive Symp. PGS	-0.029***	-0.025***	-0.020***	-0.018***
Myocardial Infarc. PGS	-0.021***	-0.017***	-0.009*	-0.006
Coronary Disease PGS	-0.011*	-0.009	-0.007	-0.006
BMI PGS	-0.033***	-0.031***	-0.020***	-0.019***
Height PGS	0.026**	0.020*	0.000	-0.004

Table V
Regression of Economic Outcomes on Investor Characteristics Used in Previous Studies

Panel A reports 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 the control variables (indicator variables for HRS waves, gender, age, married, and retired) and each of the 11 investor characteristics individually (i.e., 66 regressions for 11 explanatory variables times six outcomes). Panel B reports results from regressions of the outcome variables on the control variables and the 11 explanatory variables simultaneously. 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.

	Equity participation	%Equity	Risk aversion	$P(R_m > 0)$	$P(R_m > 20\%)$	$P(R_m < -20\%)$
Panel A: Outcomes on controls and investor characteristics individually						
ln(Wealth)	0.218***	0.120***	-0.128***	4.853***	0.340	-2.514***
ln(Income)	0.140***	0.078***	-0.101***	3.263***	-0.140	-1.271***
Education	0.139***	0.081***	-0.151***	4.703***	-0.344	-1.097***
Cognition	0.121***	0.068***	-0.128***	4.451***	-0.760**	-1.078***
Trust	0.092***	0.052***	-0.090***	4.011***	0.555**	-1.771***
Sociability	0.073***	0.040***	-0.149***	2.306***	-0.233	-0.808***
Optimism	0.090***	0.053***	-0.199***	3.858***	0.528**	-1.309***
Poor	-0.051***	-0.020***	0.024	-0.833***	-0.116	0.711***
Height	0.016***	0.008*	-0.059***	0.456	-0.579**	-0.049
BMI	-0.049***	-0.018***	0.035***	-0.454	0.263	0.570**
Health	0.110***	0.047***	-0.154***	3.421***	0.457*	-1.655***
Panel B: Outcomes on controls and all 11 investor characteristics simultaneously						
ln(Wealth)	0.175***	0.102***	-0.032*	2.762***	0.513	-1.943***
ln(Income)	0.033***	0.021***	-0.028**	0.582*	-0.344	0.069
Education	0.042***	0.025***	-0.069***	2.033***	-0.082	0.409
Cognition	0.035***	0.021***	-0.021	1.675***	-1.293***	-0.416
Trust	0.030***	0.016***	0.041**	1.905***	0.742**	-1.359***
Sociability	0.007	0.005	-0.073***	0.152	-0.129	-0.035
Optimism	-0.002	0.012	-0.133***	0.868**	0.330	0.260
Poor	-0.017***	0.000	-0.018	0.108	-0.123	0.488*
Height	-0.007	-0.001	-0.033**	-0.154	-0.494*	0.151
BMI	0.000	0.008	-0.003	0.879***	0.536*	-0.309
Health	0.033***	0.009*	-0.086***	1.511***	0.840***	-0.679**
R^2	31.29%	15.72%	9.61%	10.74%	1.32%	3.69%
Number of clusters	4,313	3,776	4,313	4,313	4,313	4,313
Number of obs.	9,840	8,061	9,840	9,840	9,840	9,840

Table VI
Regression of Investor Characteristics used in Previous Studies on Polygenic Scores (PGSs) for Cognition, Personality, Health, and Body Shape

Panel A reports coefficients from regressions of each of the 11 investor characteristics on the control variables (indicator variables for HRS waves, gender, age, married, and retired), the first 10 principal components of the genetics data, and each of the eight PGSs individually. Panel B reports coefficients when including all eight PGSs as regressors simultaneously. 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.

	ln(Wealth)	ln(Inc.)	Education	Cognition	Trust	Social	Optimism	Poor	Height	BMI	Health
	Panel A: Investor characteristics on individual PGS (+control variables and 10 principal components)										
Edu. Attainment PGS	0.136***	0.100***	0.230***	0.178***	0.136***	0.071***	0.124***	-0.045***	0.047***	-0.063***	0.103***
Gen. Cognition PGS	0.027*	0.033***	0.096***	0.102***	0.057***	-0.012	0.023	0.006	0.007	-0.017	0.040***
Neuroticism PGS	-0.060***	-0.018	-0.083***	-0.094***	-0.116***	-0.060***	-0.123***	0.057***	0.009	-0.012	-0.073***
Depressive Symp. PGS	-0.054***	-0.018*	-0.054***	-0.050***	-0.083***	-0.060***	-0.103***	0.037**	-0.006	0.000	-0.069***
Myocardial Infarc. PGS	-0.050***	-0.035***	-0.064***	-0.055***	-0.038**	0.002	-0.051***	0.022	-0.042***	0.038***	-0.070***
Coronary Disease PGS	-0.035***	-0.028***	-0.042***	-0.011	-0.004	-0.011	-0.015	0.011	-0.013	0.007	-0.043***
BMI PGS	-0.076***	-0.049***	-0.060***	-0.057***	-0.075***	-0.010	-0.059***	0.043***	-0.015	0.278***	-0.093***
Height PGS	0.050*	0.018	0.080***	0.070**	0.019	0.034	0.061*	-0.053*	0.703***	-0.001	0.035
	Panel B: Investor characteristics on all eight PGS (+control variables and 10 principal components)										
Edu. Attainment PGS	0.117***	0.090***	0.207***	0.150***	0.107***	0.067***	0.097***	-0.031*	0.018	-0.019	0.071***
Gen. Cognition PGS	-0.006	0.010	0.046***	0.064***	0.028	-0.030*	-0.006	0.019	-0.028*	0.010	0.014
Neuroticism PGS	-0.022	0.002	-0.036*	-0.062***	-0.076***	-0.024	-0.071***	0.044**	0.028	-0.004	-0.036**
Depressive Symp. PGS	-0.024	-0.004	-0.005	0.003	-0.033*	-0.042**	-0.056***	0.012	0.003	-0.013	-0.036**
Myocardial Infarc. PGS	-0.026*	-0.018	-0.036**	-0.043***	-0.026	0.017	-0.037**	0.012	-0.023	0.012	-0.046***
Coronary Disease PGS	-0.009	-0.010	-0.002	0.026	0.021	-0.012	0.014	0.000	0.016	-0.011	-0.012
BMI PGS	-0.050***	-0.029***	-0.014	-0.022	-0.051***	0.000	-0.036**	0.037**	-0.004	0.275***	-0.072***
Height PGS	0.021	-0.002	0.031	0.033	-0.011	0.023	0.033	-0.043	0.704***	0.010	0.006
R^2	13.11%	22.68%	12.36%	15.33%	7.17%	4.31%	6.81%	1.83%	17.79%	8.07%	6.74%
Number of clusters	5,513	5,513	5,513	4,825	5,080	5,059	5,217	5,512	5,513	5,491	5,513
Number of obs.	12,555	12,555	12,555	11,061	11,554	11,507	11,862	12,552	12,555	12,468	12,553

Table VII

Identifying Investor Characteristic Channels linking Polygenic Score (PGS) to Economic Outcomes

The first column in Panel A reports coefficients from regressions of stock market participation on the control variables (indicator variables for HRS waves, gender, age, married, and retired), the first 10 principal components of the genetics data, and each of the eight PGSs individually. 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 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.

Variable:	None	ln(Wlth.)	ln(Inc.)	Educ.	Cog.	Trust	Social	Optim.	Poor	Height	BMI	Health
Panel A: Equity participation on control variables (+10 principal components), individual investor characteristics, and individual PGSs												
Edu. PGS	0.065***	0.036***	0.052***	0.035***	0.042***	0.053***	0.060***	0.053***	0.063***	0.064***	0.063***	0.054***
Cog. PGS	0.022***	0.016***	0.017***	0.009	0.007	0.015**	0.020***	0.019***	0.022***	0.022***	0.021***	0.018***
Neuro. PGS	-0.038***	-0.025***	-0.035***	-0.026***	-0.027***	-0.028***	-0.036***	-0.028***	-0.035***	-0.038***	-0.038***	-0.030***
Depres. PGS	-0.029***	-0.018***	-0.027***	-0.022***	-0.024***	-0.021***	-0.026***	-0.018***	-0.028***	-0.029***	-0.030***	-0.022***
M. Infarc. PGS	-0.021***	-0.010*	-0.016***	-0.012**	-0.014**	-0.015**	-0.019***	-0.015**	-0.020***	-0.020***	-0.020***	-0.014**
Coronary PGS	-0.011*	-0.003	-0.007	-0.005	-0.007	-0.008	-0.010	-0.008	-0.010*	-0.011*	-0.011*	-0.006
BMI PGS	-0.033***	-0.017***	-0.027***	-0.025***	-0.028***	-0.026***	-0.032***	-0.028***	-0.031***	-0.033***	-0.022***	-0.023***
Height PGS	0.026**	0.015	0.023**	0.015	0.013	0.019	0.012	0.016	0.023**	0.015	0.027**	0.022**
Panel B: %Equity on control variables (+10 principal components), individual investor characteristics, and individual PGSs												
Edu. PGS	0.039***	0.024***	0.033***	0.023***	0.031***	0.032***	0.035***	0.033***	0.039***	0.039***	0.039***	0.036***
Cog. PGS	0.017***	0.016***	0.016***	0.011*	0.009	0.017***	0.019***	0.019***	0.018***	0.017***	0.017***	0.016***
Neuro. PGS	-0.017***	-0.009	-0.015**	-0.011*	-0.011*	-0.012*	-0.015**	-0.011*	-0.016**	-0.017***	-0.017***	-0.014**
Depres. PGS	-0.020***	-0.015***	-0.019***	-0.017***	-0.020***	-0.014***	-0.018***	-0.014***	-0.019***	-0.020***	-0.020***	-0.018***
M. Infarc. PGS	-0.009*	-0.004	-0.008	-0.004	-0.008	-0.006	-0.008	-0.005	-0.009*	-0.009*	-0.009*	-0.007
Coronary PGS	-0.007	-0.004	-0.006	-0.004	-0.010*	-0.007	-0.009*	-0.007	-0.007	-0.007	-0.007	-0.006
BMI PGS	-0.020***	-0.011**	-0.017***	-0.015***	-0.018***	-0.015***	-0.018***	-0.016***	-0.019***	-0.020***	-0.016***	-0.016***
Height PGS	0.000	-0.003	0.000	-0.005	0.005	-0.002	-0.008	-0.006	0.000	-0.007	0.001	0.000
Panel C: Risk Aversion on control variables (+10 principal components), individual investor characteristics, and individual PGSs												
Edu. PGS	-0.044***	-0.027*	-0.035**	-0.010	-0.027*	-0.031**	-0.028*	-0.016	-0.043***	-0.041***	-0.041***	-0.029*
Cog. PGS	-0.025	-0.021	-0.022	-0.010	-0.017	-0.019	-0.023	-0.018	-0.025	-0.025	-0.028*	-0.019
Neuro. PGS	0.079***	0.071***	0.077***	0.067***	0.085***	0.067***	0.065***	0.052***	0.077***	0.079***	0.079***	0.068***
Depres. PGS	0.031**	0.024*	0.029**	0.023	0.029*	0.022	0.021	0.009	0.030**	0.031**	0.032**	0.020
M. Infarc. PGS	0.021	0.014	0.017	0.011	0.016	0.024	0.022	0.012	0.020	0.018	0.019	0.010
Coronary PGS	0.043***	0.039***	0.041***	0.037**	0.042***	0.041***	0.041***	0.038***	0.043***	0.043***	0.043***	0.037***
BMI PGS	-0.001	-0.011	-0.006	-0.010	0.001	-0.006	0.002	-0.010	-0.002	-0.002	-0.013	-0.015
Height PGS	-0.051**	-0.045*	-0.050*	-0.040	-0.048*	-0.048*	-0.033	-0.035	-0.050*	-0.013	-0.051*	-0.046*

Table VII (continued)

Identifying Investor Characteristic Channels linking Polygenic Score (PGS) to Economic Outcomes

Variable:	None	ln(Wlth.)	ln(Inc.)	Educ.	Cog.	Trust	Social	Optim.	Poor	Height	BMI	Health
Panel D: P(R_m>0) on control variables (+10 principal components), individual investor characteristics, and individual PGSs												
Edu. PGS	1.816***	1.185***	1.516***	0.784**	1.031***	1.278***	1.596***	1.257***	1.784***	1.793***	1.778***	1.478***
Cog. PGS	0.707**	0.576*	0.602*	0.259	0.253	0.429	0.682**	0.569*	0.711**	0.703**	0.707**	0.570*
Neuro. PGS	-0.958***	-0.671*	-0.899**	-0.573	-0.574	-0.848**	-1.063***	-0.672*	-0.914**	-0.963***	-0.974***	-0.709*
Depres. PGS	-0.461	-0.203	-0.402	-0.209	-0.238	-0.226	-0.390	-0.114	-0.431	-0.457	-0.462	-0.227
M. Infarc. PGS	-1.095***	-0.859***	-0.985***	-0.800***	-0.948***	-0.886***	-1.087***	-0.873***	-1.078***	-1.072***	-1.059***	-0.861***
Coronary PGS	0.012	0.180	0.101	0.208	0.157	0.071	-0.005	0.056	0.021	0.020	0.029	0.163
BMI PGS	-0.373	-0.010	-0.218	-0.093	-0.104	-0.250	-0.413	-0.232	-0.339	-0.364	-0.275	-0.058
Height PGS	0.776	0.538	0.717	0.404	0.415	0.505	0.385	0.337	0.735	0.430	0.832	0.650
Panel E: P(R_m>0.2) on control variables (+10 principal components), individual investor characteristics, and individual PGSs												
Edu. PGS	-0.452*	-0.503*	-0.438	-0.382	-0.347	-0.526*	-0.448	-0.579**	-0.455*	-0.432	-0.466*	-0.503*
Cog. PGS	-0.597**	-0.606**	-0.592**	-0.564*	-0.432	-0.636**	-0.613**	-0.657**	-0.598**	-0.594**	-0.605**	-0.617**
Neuro. PGS	0.743**	0.763**	0.740**	0.714**	0.524	0.681**	0.609*	0.677**	0.746**	0.747**	0.758**	0.780**
Depres. PGS	0.286	0.303	0.283	0.266	0.157	0.300	0.226	0.243	0.288	0.283	0.300	0.319
M. Infarc. PGS	-0.195	-0.180	-0.201	-0.220	-0.341	-0.168	-0.168	-0.181	-0.192	-0.214	-0.218	-0.162
Coronary PGS	0.228	0.239	0.223	0.212	0.290	0.200	0.148	0.203	0.227	0.223	0.233	0.249
BMI PGS	0.217	0.242	0.209	0.195	0.226	0.165	0.208	0.231	0.221	0.210	0.156	0.263
Height PGS	-0.322	-0.338	-0.319	-0.292	-0.193	-0.241	-0.437	-0.386	-0.322	-0.011	-0.296	-0.339
Panel F: P(R_m<-0.2) on control variables (+10 principal components), individual investor characteristics, and individual PGSs												
Edu. PGS	-0.735***	-0.408	-0.623**	-0.522*	-0.553*	-0.460*	-0.654**	-0.498*	-0.709***	-0.729***	-0.689***	-0.573**
Cog. PGS	-0.877***	-0.810***	-0.838***	-0.782***	-0.691**	-0.875***	-0.930***	-0.897***	-0.877***	-0.876***	-0.876***	-0.811***
Neuro. PGS	1.166***	1.021***	1.145***	1.085***	1.146***	1.162***	1.261***	1.209***	1.137***	1.168***	1.183***	1.050***
Depres. PGS	0.618**	0.487&	0.596**	0.563**	0.592**	0.559**	0.679**	0.595**	0.597**	0.617**	0.625**	0.507*
M. Infarc. PGS	-0.058	-0.180	-0.100	-0.125	-0.019	-0.206	-0.100	-0.133	-0.074	-0.065	-0.099	-0.175
Coronary PGS	-0.163	-0.249	-0.197	-0.207	-0.062	-0.260	-0.151	-0.175	-0.166	-0.165	-0.178	-0.235
BMI PGS	0.337	0.152	0.280	0.276	0.270	0.156	0.352	0.263	0.310	0.335	0.185	0.186
Height PGS	-0.455	-0.333	-0.433	-0.372	-0.188	-0.271	-0.171	-0.094	-0.430	-0.397	-0.519	-0.398

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

Each of the outcome variables (risk aversion, beliefs regarding the distribution of equity returns, and equity participation measures) is regressed on the control variables (indicator variables for HRS waves, gender, age, married, and retired) and the first 10 principal components of the genetics data. We define the residuals from these regressions as the orthogonalized outcome variables. Panel A reports regressions of orthogonalized equity market participation on orthogonalized risk-aversion and orthogonalized beliefs. 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.

	Equity participation					%Equity				
	Panel A: Equity market participation on risk aversion and beliefs regarding expected return distribution									
Risk aversion	-0.048***				-0.040***	-0.035***				-0.029***
$P(R_m > 0)$		0.089***			0.098***		0.065***			0.070***
$P(R_m > 20\%)$			0.018***		-0.035***			0.015***		-0.021***
$P(R_m < -20\%)$				-0.046***	-0.023***				-0.033***	-0.015***
R^2	1.08%	3.64%	0.15%	1.00%	5.12%	0.86%	3.01%	0.16%	0.77%	4.09%
	Panel B: Equity market participation on portion of risk aversion and beliefs related to PGSs and portion orthogonal to PGSs									
Risk aversion PGS	-0.048***				0.013	-0.022***				0.011
$P(R_m > 0)$ PGS		0.061***			0.065***		0.030***			0.028***
$P(R_m > 20\%)$ PGS			-0.043***		-0.047**			-0.029***		-0.029***
$P(R_m < -20\%)$ PGS				-0.052***	0.021				-0.025***	0.005
Risk aversion non-PGS	-0.045***				-0.037***	-0.033***				-0.028***
$P(R_m > 0)$ non-PGS		0.084***			0.092***		0.063***			0.066***
$P(R_m > 20\%)$ non-PGS			0.020***		-0.030***			0.016***		-0.018***
$P(R_m < -20\%)$ non-PGS				-0.044***	-0.022***				-0.032***	-0.015***
R^2	1.99%	4.99%	1.03%	2.15%	6.46%	1.14%	3.45%	0.80%	1.16%	4.72%
$\%R^2$ due to PGS	53.54%	34.43%	82.39%	58.78%	30.31%	30.31%	18.93%	76.48%	38.86%	20.27%

Table IX
The Role of the Eight PGSs in Linking Investor Characteristics to Economic Outcomes

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) are regressed on the control variables (indicator variables for HRS waves, gender, age, married, and retired) and the first 10 principal components of the genetics data. We define the residuals from these regressions as the orthogonalized outcome variables and the orthogonalized investor characteristic variables. Each orthogonalized outcome variable is regressed on the portion of orthogonalized investor characteristic variable predicted by the eight PGSs and the portion of the orthogonalized traditional explanatory variable independent of the eight PGSs. 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.

Table IX (continued)
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)	0.069***	0.197***	0.039***	0.099***	-0.050***	-0.114***	1.748***	4.318***	-0.467*	0.362	-0.788***	-2.229***
ln(Income)	0.066***	0.116***	0.039***	0.061***	-0.047***	-0.084***	1.751***	2.644***	-0.457*	-0.112	-0.730***	-0.989***
Education	0.066***	0.122***	0.038***	0.070***	-0.054***	-0.136***	1.887***	4.182***	-0.525**	-0.261	-0.874***	-0.831***
Cognition	0.064***	0.103***	0.038***	0.055***	-0.062***	-0.108***	1.928***	3.875***	-0.531*	-0.633**	-0.979***	-0.837***
Trust	0.068***	0.081***	0.038***	0.045***	-0.053***	-0.080***	1.888***	3.670***	-0.514**	0.645**	-1.086***	-1.579***
Sociability	0.058***	0.066***	0.029***	0.036***	-0.046***	-0.143***	1.286***	2.124***	-0.403	-0.238	-0.705***	-0.702***
Optimism	0.065***	0.080***	0.034***	0.046***	-0.051***	-0.188***	1.757***	3.592***	-0.435*	0.628**	-0.941***	-1.179***
Poor	-0.062***	-0.045***	-0.029***	-0.017***	0.050***	0.020	-1.504***	-0.695**	0.446*	-0.128	0.817***	0.631**
Height	0.022***	0.013**	0.007	0.008	-0.026*	-0.051***	0.910***	0.377	-0.089	-0.428*	-0.238	-0.111
BMI	-0.034***	-0.041***	-0.020***	-0.012**	0.001	0.034**	-0.463	-0.292	0.225	0.231	0.343	0.473*
Health	0.065***	0.098***	0.036***	0.040***	-0.049***	-0.144***	1.596***	3.117***	-0.464*	0.511**	-0.811***	-1.506***
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)	20.12%		7.96%		1.61%		3.24%		0.07%		1.07%	
ln(Income)	8.30%		3.74%		0.96%		1.50%		0.04%		0.29%	
Education	8.90%		4.49%		2.23%		3.14%		0.07%		0.28%	
Cognition	6.74%		3.19%		1.61%		2.76%		0.13%		0.32%	
Trust	5.22%		2.44%		0.95%		2.55%		0.13%		0.71%	
Sociability	3.62%		1.56%		2.33%		0.92%		0.04%		0.19%	
Optimism	4.94%		2.32%		3.95%		2.39%		0.12%		0.44%	
Poor	2.75%		0.81%		0.30%		0.41%		0.04%		0.20%	
Height	0.31%		0.08%		0.34%		0.14%		0.04%		0.01%	
BMI	1.31%		0.39%		0.12%		0.04%		0.02%		0.07%	
Health	6.38%		2.03%		2.40%		1.83%		0.09%		0.56%	
Panel C: Fraction of regression R^2 explained by portion of investor characteristics variable predicted by the PGSs												
ln(Wealth)	10.85%		13.43%		16.25%		14.08%		62.41%		11.13%	
ln(Income)	24.69%		28.44%		24.27%		30.50%		94.32%		35.31%	
Education	22.95%		22.79%		13.58%		16.92%		80.14%		52.52%	
Cognition	27.86%		32.92%		24.78%		19.84%		41.30%		57.77%	
Trust	41.47%		41.43%		30.76%		20.93%		38.80%		32.09%	
Sociability	43.64%		39.84%		9.27%		26.83%		74.18%		50.20%	
Optimism	40.27%		35.23%		6.88%		19.31%		32.46%		38.93%	
Poor	65.62%		74.18%		86.44%		82.39%		92.35%		62.62%	
Height	73.44%		41.76%		19.82%		85.38%		4.12%		82.12%	
BMI	41.40%		72.65%		0.15%		71.50%		48.64%		34.44%	
Health	30.57%		44.36%		10.35%		20.78%		45.23%		22.49%	
Average	38.43%		40.64%		22.05%		37.13%		55.81%		43.60%	