Why Do Individuals Exhibit Investment Biases?*

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Abstract

For a long list of investment "biases," e.g., home bias, loss aversion, and performance chasing, we find that genetic differences explain up to 45% of the variation across individual investors. The genetic factors that influence investment biases are also found to affect behaviors in other, non-investment, domains. This evidence is consistent with a view that investment biases are manifestations of innate and evolutionary ancient features of human behavior. The environment an investor experiences also affects investment biases, either directly or as a moderator of genetic predispositions. For example, we find that work-related experience with finance seems to reduce genetic predispositions to investment biases, while general education does not. Finally, even genetically identical investors, who grow up in the same family environment, often differ substantially in their investment behaviors due to individual-specific experiences or events.

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I Introduction

The list of investment "biases" that individual investors exhibit is long. They lack diversification and have a preference for familiar investments (French and Poterba (1991) and Huberman (2001)), trade too much (Odean (1999)), are reluctant to realize their losses (Odean (1998) and Dhar and Zhu (2006)), extrapolate recent superior returns (Benartzi (2001)), and have a preference for skewness and lottery-type investments (Kumar (2009)). These behaviors have previously been partially attributed to mechanisms rooted in psychology research: Ambiguity aversion and familiarity for lack of diversification (Ellsberg (1961) and Heath and Tversky (1991)), overconfidence for excessive trading (Griffin and Tversky (1992)), loss aversion and mental accounting for the reluctance to realize losses (Kahneman and Tversky (1979) and Thaler (1985)), representativeness and the hot hands fallacy for excessive extrapolation of past returns (Tversky and Kahneman (1974)), and cumulative prospect theory for skewness preferences (Tversky and Kahneman (1992)).[1]

While the previously referenced studies have shown that individual investors, on average, exhibit these investment biases, little research has been devoted to understanding why investors exhibit these behaviors or why some investors are more biased than others. Are investors born with certain predispositions that manifest themselves as investment biases? Or do investors exhibit biases as a result of parenting or individual-specific experiences or events? The origins of investment biases have potentially important implications for the extent to which education and market incentives may be expected to reduce investment biases and also for the design of public policy.

We use standard empirical methodology adopted from quantitative behavioral genetics research (see Neale and Maes (2004) for an overview), which has recently been used also in finance research (e.g., Barnea, Cronqvist, and Siegel (2010) and Cesarini et al. (2010)). Our data set from the world's largest twin registry, the Swedish Twin Registry (STR), matched with detailed data on the twins' investment behaviors, enables us to decompose differences across individuals into genetic versus environmental components. This decomposition is based on an intuitive insight: Identical twins

[1]Throughout the paper, we will refer to these behaviors as "biases" because they constitute non-standard preferences and beliefs from the perspective of standard models used in financial economics. It is beyond the scope of this paper to provide estimates of the potential welfare losses attributed to any of these behaviors. Some of the referenced papers provide such estimates.

share 100% of their genes, while the average proportion of shared genes is only 50% for fraternal twins. If identical twins exhibit more similarity with respect to these investment behaviors than do fraternal twins, then there is evidence that these behaviors are influenced, at least in part, by genetic factors.

We can summarize our results as follows. First, for a long list of investment biases, we find that genetic differences explain up to 45% of the variation across individual investors. Consistent with a view that investment biases are manifestations of innate and evolutionary ancient features of human behavior, we find that the genetic factors that influence investment biases also affect behaviors in other, non-investment, domains. For example, the correlation between a preference for familiar stocks and familiarity preferences in other domains is due to shared genetic influences. While our results are consistent with several behavioral genetic studies that have shown significant heritability of human behavior, they provide the first direct evidence from real-world, non-experimental data that persistent investment behaviors are to a significant extent determined by genetic endowments. Such evidence provides support for evolutionary arguments that behaviors which manifest themselves as investment biases in today's financial markets have survived because they were advantageous in evolutionary ancient times (e.g., Rayo and Becker (2007) and Brennan and Lo (2011)).

The relative importance of genetic relative to environmental factors is found to vary across different investors. Most importantly, among investors with work-related experience with finance, we find a significant reduction of the relative amount of genetic variation, which is consistent with the notion that practical experience in finance moderates genetic predispositions. We cannot rule out, though, that the selection of profession reduces the relevant genetic variation in this sub-sample. Controlling for selection, we also investigate the role of general education, measured as years of educations, in moderating the relative importance of genetic factors. We find that general education does not reduce the relative importance of genetic factors in explaining investment biases.

Finally, we find that even genetically identical investors who grew up in the same family environment differ substantially in terms of their investment behaviors. Individual-specific environments, experiences, or events must therefore play an important role in shaping individuals' investment choices. Examining differences between investment biases of genetically identical investors, we show

how genetically informed data, such as twin data used in this study, can be used to better assess the causal impact of individual-specific factors, such as education.

The paper is organized as follows. Section II reviews related research. Section III describes our data sources, reports summary statistics, and defines our measures of investment biases. Section IV describes our empirical methodology. Sections V and VI report our results and robustness checks. Section VII concludes.

II The Origins of Investment Biases

A Genetic Origins

A.1 Models of the Evolution of Behavior

The literature on the evolution of behavior is large, and includes disciplines such as biology, evolutionary psychology, and economics. It is beyond the scope of this paper to review this literature. For extensive reviews, we refer to Robson (2001), Rayo and Becker (2007), Brennan and Lo (2011), and the examples and references therein. Underlying this literature is the assumption that some of the variation in behavior is due to genetic differences. Over time, those behaviors that confer greater "fitness", i.e. reproductive success, become more common in the population. The outcome of this natural selection process, of course, depends on the environment as different behaviors will have more or less reproductive success in different environments.

Behaviors and psychological mechanisms that manifest themselves as investment biases in modern financial markets, could be widespread today, because they were associated with a *reproductive* advantage relative to alternative behaviors over the course of human development. That is, evolution might have selected behaviors that were fitness maximizing in evolutionary ancient times, but may not be optimal in all relevant domains today (e.g., Waldman (1994) and Rayo and Becker (2007)). Rayo and Becker (2007), for example, argue (p. 304):

> "[W]hen talking about fitness-maximizing [utility] functions, we refer to functions that optimized genetic multiplication during hunter-gatherer times (before agriculture and animal domestication were developed). In modern times, on the other hand, we presumably share most of the innate characteristics of our hunter-gatherer ancestors. But since the technological landscape has

> changed so rapidly since the rise of agriculture, our [utility] functions need no longer optimally promote the present multiplication of our genes."

For example, in a hunter-gatherer society it may generally have been harmful for humans to explore or invest in the unfamiliar, which may explain a strong preference for investing in the familiar even today (e.g., Benartzi (2001) and Huberman (2001)). Johnson and Fowler (2011) show in a formal model that for a wide range of settings overconfidence, essentially an error of judgement with respect to one's qualities and capabilities, can lead to higher "net-payoffs" in competition for resources and might therefore have been favored by evolution. As a consequence, individual investors today might "suffer" from overconfidence in their trading decisions as their behavior is to some extent shaped by genetic endowments that they share with their ancient ancestors.[2] Brennan and Lo (2011) and McDermott, Fowler, and Smirnov (2008) provide similar arguments for the evolution of loss aversion and prospect theory preferences.

In general, different behaviors can survive and exist in a population as long as they lead to similar reproductive success. For example, if most individuals have a preference for the familiar, the benefit of exploring the unfamiliar might be sufficiently high to compensate for the additional risk. Alternatively, as Brennan and Lo (2011) point out, heterogeneity in behavior could also be due to systematic environmental risks:

> "If environmental risks are systematic, survival depends on the population diversifying its behavior so that some fraction will survive to reproduce no matter what the environment is like. In such cases, it may seem as if certain individuals are acting irrationally since they may not be acting optimally for a given environment. But such heterogeneous behavior is, in fact, optimal from the perspective of the population."

In summary, evolutionary models of behavior imply that variation of behavior across individuals is partly due to genetic differences between those individuals. Behavioral biases can survive and become widespread due to the reproductive advantage they have conferred over the course of human evolution.

[2] Interestingly, Hirshleifer and Luo (2001) argue that even in today's financial markets overconfident investors can do better than rational investors as they exploit mispricing more aggressively.

A.2 Empirical Evidence

Table 1 reviews research that links investment biases to psychological mechanisms, and then lists twin and gene candidate studies that link these mechanisms to genetic variation across individuals.

Diversification and Home Bias. Investors often diversify their portfolios less than is recommended by standard models. For example, they overweight stocks from their home market (e.g., French and Poterba (1991)). This home bias has not been easy to explain (e.g., Lewis (1999)). Ambiguity aversion and familiarity (e.g., Heath and Tversky (1991) and Fox and Tversky (1995)) is an alternative approach to explain lack of diversification. The recent gene association study by Chew et al. (2011) identifies several specific genes that affect ambiguity aversion and familiarity.

Turnover. One important stylized facts about individual investors is that they often trade too much (e.g., Odean (1999), Barber and Odean (2000), and Barber, Lee, Liu, and Odean (2009)). Excessive trading has been found to be related to individual characteristics that are partly genetic, such as overconfidence and sensation seeking (e.g., Barber and Odean (2001) and Grinblatt and Keloharju (2009)). Twin studies have documented that both overconfidence and sensation-seeking are partially genetic (Cesarini et al. (2009) and Fulker et al. (1980)). More recent research links sensation seeking to specific genes (Derringer et al. (2010)).

Disposition Effect. Shefrin and Statman (1985) argue that a combination of mental accounting (Thaler, 1985) and prospect theory preferences similar to those in Kahneman and Tversky (1979) makes investors more likely to sell stocks with a gain than with a loss. The recent gene association study by Zhong et al. (2009) identifies the specific genes that affect the concavity and convexity of the prospect theory value function in the gain and loss domains. Furthermore, loss aversion has been found also in animals that are genetically close to humans. Chen, Lakshminarayanan, and Santos (2006) show that capuchin monkeys, which lack experience with markets and finance, exhibit loss aversion: "[L]oss aversion is an innate and evolutionarily ancient feature of human preferences, a function of decision-making systems that evolved before the common ancestors of capuchins and humans diverged" (Chen et al. (2006), p. 520). Finally, Harbaugh, Krause, and Vesterlund (2001) find evidence of loss aversion in children as young as five, and there is no evidence that the behavior disappears significantly with age, at least not through college age. This result also suggests that loss aversion is genetic, assuming that these children do not learn such behavior before age five. Twin studies have also documented that loss aversion is partially genetic (e.g., Cesarini et al. (2012)).

Performance Chasing. Individual investors often extrapolate recent good stock or fund performance even when it shows little to no persistence (e.g., Patel, Zeckhauser, and Hendricks (1991) and Benartzi (2001)). In their work on representativeness, Tversky and Kahneman (1974) find that people expect that a sequence of outcomes generated by a random process will resemble the essential characteristics of that process even when the sequence is short. Griffin and Tversky (1992) provide an extension documenting that people focus on the strength or extremeness of the evidence with insufficient regard of its credence, predictability, and weight. In contrast to the other investment biases we study, we are not aware of much existing research that directly links excessive extrapolation to specific genes.

Skewness Preference. Investors often exhibit a preference for positive skewness, i.e., lottery-type investments (e.g., Kumar (2009)). Such behavior is expected if investors make decisions based on cumulative prospect theory (Tversky and Kahneman (1992) and Barberis and Huang (2008)). Twin studies have found that the preference to gamble are partially genetic (e.g., Slutske et al. (2000)). Furthermore, the recent gene association study by Zhong et al. (2009) finds that a specific gene results in a preference for gambles with a small probability of a very large payoff.

B Environmental Origins

While the evolutionary models of behavioral biases imply that behavioral variation across individuals reflects, to some extent, genetic differences, alternative models of the origin of behavior emphasize environmental factors. For example, in models of "direct vertical socialization" children are born without defined preferences, and they are first exposed to their parents' socialization. If parent-child socialization does not succeed, the child is influenced by a random role model in the population (e.g., teachers, co-workers, etc.). These models have been used to explain parent-child similarity with respect to, e.g., religion (e.g., Bisin and Verdier (2000)), but may extend to the investment domain.

The environment may influence investment biases in other ways than through parenting and upbringing. For example, in the model by Gervais and Odean (2001) individual investors learn to be biased by becoming overconfident because of their past idiosyncratic investment successes.

While we are not aware of direct empirical tests of the above models with respect to behavioral biases, a growing empirical literature examines the circumstances and events that may reduce the behavioral biases that investors display. The evidence so far suggests that wealthier, more educated, and generally more sophisticated investors make better financial decisions and exhibit fewer investment biases (e.g., Dhar and Zhu (2006), Kumar (2009), Calvet, Campbell, and Sodini (2009)). The identified characteristics of less biased investors do not exclusively represent environmental effects, but also reflect to varying degrees genetic differences across investors. Separating the two and identifying effective intervention is, of course, important from a policy perspective and an area of active research (e.g. Bhattacharya et al. (2012)).

III Data

A Data Sources

Our data set is constructed by matching a large number of twins from the Swedish Twin Registry (STR), the world's largest twin registry, with data from individual tax filings and other databases by Statistics Sweden. In Sweden, twins are registered at birth, and the STR collects additional data through in-depth interviews.[3] Importantly, STR's data provide us with the zygosity of each twin pair: Identical or "monozygotic" (MZ) twins are genetically identical, while fraternal or "dizygotic" (DZ) twins are genetically different, and share on average 50% of their genes.[4]

Until 2007, taxpayers in Sweden were subject to a wealth tax. Prior to the abolishment of this tax, all Swedish banks, brokerage firms, and other financial institutions were required by law to report to the Swedish Tax Authority information about individuals' portfolios (i.e., stocks, bonds,

[3] STR's databases are organized by birth cohort. The Screening Across Lifespan Twin, or "SALT," database contains data on twins born 1886–1958. The Swedish Twin Studies of Adults: Genes and Environment database, or "STAGE," contains data on twins born 1959–1985. In addition to twin pairs, twin identifiers, and zygosity status, the databases contain variables based on STR's telephone interviews (for SALT), completed 1998–2002, and combined telephone interviews and Internet surveys (for STAGE), completed 2005–2006. For further details about STR, we refer to Lichtenstein et al. (2006).

[4] Zygosity is based on questions about intrapair similarities in childhood. One of the questions was: Were you and your twin partner during childhood "as alike as two peas in a pod" or were you "no more alike than siblings in general" with regard to appearance? STR has validated this method with DNA analysis as having 98 percent accuracy on a subsample of twins. For twin pairs for which DNA has been collected, zygosity status is based on DNA analysis.

mutual funds, derivatives, and other securities) held as of December 31 and also all sales transactions during the year.

We have matched the twins with portfolio and sales transaction data between 1999 and 2007, providing us with detailed information on investment behavior. For each individual, our data set contains all securities held at the end of the year (identified by each security's International Security Identification Number (ISIN)), the number of each security held, the dividends received during the year, and the end of the year value. We also have data on which securities were sold over the year, and in the case of stocks, the number of securities sold and the sales price.[5] Security level data have been collected from several sources, including Bloomberg, Datastream, Morningstar, SIX Telekurs, Standard & Poor's, and the Swedish Investment Fund Association.

B Sample Selection and Summary Statistics

We follow prior research on investment biases by analyzing equity investments, i.e., individual stocks as well as equity and mixed mutual funds, with a particular focus on individual stocks. We therefore exclude individuals who do not participate in equity markets. Our empirical methodology also requires that we exclude incomplete pairs of twins.

We have 15,208 adult twin pairs in which each twin has at least one year of non-missing equity investment data. Panel A of Table 2 reports summary statistics for our data set, which includes 30,416 individuals. Opposite-sex twins are the most common (37%); identical male twins are the least common (13%). The distribution in the table is consistent with what would be expected from large samples of twins (e.g., Bortolus et al. (1999)).

Table 2 Panel B reports summary statistics separately for identical and fraternal twins. Socioeconomic characteristics are averaged over those years an investor is in our data set.[6] While identical and fraternal twins are relatively similar with respect to socioeconomic characteristics, we observe substantial cross-sectional variation. We find that the average (median) investor holds about 4 (2)

[5]Sales transaction data are not available for 2001 and 2002, and we do not have the exact dates of any of the sales transactions in our data set.

[6]The educational variables are based on the maximum, not an average.

equity securities with a combined value of about $20,000 ($4,000) in the portfolio.[7] About 80% hold at least one equity mutual fund, and about 40% hold at least one stock. Finally, we have verified that the socioeconomic characteristics of the twins in our sample are similar to non-twins of the same age and gender who participate in the equity market (not tabulated).

C Measures of Investment Behaviors

In this subsection, we define our measures of investment behaviors. Appendix Table A1 reports detailed definitions and Table 3 reports summary statistics for direct stock holdings as well as all equity investments consisting of direct stock as well as mutual fund holdings.

For direct stock holdings, we measure *Diversification* as the number of distinct stocks held in an individual's portfolio at the end of a given year. For holdings of stocks and mutual funds, we follow Calvet et al. (2009) and define *Diversification* as the proportion of equity investments invested in mutual funds as opposed to individual stocks. To reduce measurement error, we calculate the equally weighted average *Diversification* across all years the individual is in the data set. Summary statistics in Table 3 show that the average investor with direct holdings of stocks holds about three stocks, while across all investors about 70% of their equity portfolio is invested in mutual funds.

We measure *Home Bias* by the average proportion invested in Swedish securities. Table 3 shows that for individual stocks the average home bias is 94%, but drops to about 50% once we include mutual fund investments.

We measure *Turnover*, i.e., an individual's propensity to trade and turnover the portfolio, following Barber and Odean (2000, 2001). Specifically, for direct stock holdings, we divide, for each individual investor and year, the sales volume (in Swedish krona) during the year by the value of directly held stocks at the beginning of the year. Since we do not have sales prices for mutual funds, we also construct a turnover measure using the number of sales transactions during the year divided by the number of equity securities in the investor's portfolio at the beginning of the year. For each

[7] We use the average end-of-year exchange rate 1999-2007 of 8.0179 Swedish krona per U.S. dollar to convert summary statistics. When we estimate models in Section V, all values are in Swedish krona, i.e., not converted to dollars. In terms of size, the portfolios in our data set are comparable to those in other data sets of a broad set of individual investors. For example, in Grinblatt and Keloharju (2009) the average (median) investor holds about 2 (1) equity securities with a combined value of about EUR 24,600 (EUR 1,600) in the portfolio.

measure, we compute the average turnover using all years with available data.

Table 3 reports that for the average investor in our data who holds individual stocks, annual (sales) turnover is about 20%, a magnitude similar to that reported by Agnew, Balduzzi, and Sundén (2003) for a large set of retirement savings accounts in the U.S., and Grinblatt and Keloharju (2009) for a large sample of individual investors in Finland. Even though many investors in our data trade relatively little, substantial variation exists, as indicated by the cross-sectional standard deviation of about 33%. Some of the investors in our data set therefore likely trade too much, as in, e.g., Odean (1999). That is, they trade more than what is needed to rebalance their portfolios or to satisfy liquidity needs. To control for cross-sectional variation in such reasons to trade, we follow Grinblatt and Keloharju (2009) and control for socioeconomic characteristics that may correlate with rebalancing needs and liquidity demands. The remaining variation may then be considered variation in "excessive" trading.

We measure the *Disposition Effect* in the spirit of Odean (1998) and Dhar and Zhu (2006). Specifically, at the end of each year during which we observe a sales transaction, we classify securities in an investor's portfolio as winners or losers based on the security's price relative to the approximate price at which the investor acquired the security.[8] Using data across all years with sales transactions, we calculate for each investor the the proportion of gains realized to the total number of realized and unrealized gains (PGR) as well as the proportion of losses realized to total losses (PLR). The larger the difference between PGR and PLR, the more reluctant a given investor is to realize losses.

Table 3 reveals that we are able to calculate the *Disposition Effect* only for a subset of investors. The reduction in sample size is due to missing information on purchase prices for securities that are present in an investor's portfolio before 1999, the first year of our sample period, as well as infrequent trading by some investors. The average investor exhibits a disposition effect of about 4% with respect to direct equity holdings and of about 2% when including mutual funds. Most importantly, given that the PGR – PLR difference is bounded by -1 and $+1$, the standard deviation of about 40% shows that there is significant variation across individuals with respect to the reluctance to realize losses.

[8] Since we do not observe the exact price at which an investors acquires a given security, we use the end-of-year price (averaged between the year before an acquisition and the year of the acquisition) as the reference price.

We measure *Performance Chasing* by an individual's propensity to purchase securities that have performed well in the recent past. More specifically, each year we sort stocks and equity mutual funds separately into return deciles using the returns during the year. For each investor and year with net increases in holdings of stocks or mutual funds, we calculate the fraction of purchased securities with returns in the top two deciles. The higher that fraction, the more the individual chases performance by overweighting securities with higher recent performance. *Performance Chasing* is the average fraction over all years with net acquisitions of equity securities. Table 3 shows, on average, about 10-15% of the securities acquired have shown relatively strong recent performance. Since not all investors make net acquisitions during our sample period, *Performance Chasing* is only available for a subset of investors

We measure an individual's *Skewness Preference* as in Kumar (2009). For each investor and year we calculate the proportion of the portfolio that is invested in "lottery" securities, i.e., securities with a below median price as well as above median idiosyncratic volatility and above median skewness. *Skewness Preference* is the fraction of lottery securities averaged over all years with portfolio data. Table 3 shows that, on average, about 3-4% of an investor's portfolio is held in lottery securities.

To reduce the dimensionality of some of our analysis, we also construct an index that summarizes the above investment behaviors for each investor with holdings of individual stocks. Specifically, for each of the investment behaviors, we assign a value of zero (no bias), one, or two (most biased), depending on the observed level. For example, for the *Disposition Effect*, we assign two to investors with a disposition effect over 40% (one standard deviation above zero), one to investors with a strictly positive disposition effect, and zero otherwise. Appendix Table A1 provides a detailed description of the construction of the *Investment Bias Index*. If for a given investor, a behavior is missing, we use the median behavior to assign the bias index component (zero, one, or two). An individual's *Investment Bias Index* is the sum across all the investment behaviors and takes on values between zero and twelve.

IV Empirical Methodology

To decompose the cross-sectional variation in investment behaviors into genetic and environmental components, we model each measure of an investment bias y_{ij} for twin j (1 or 2) of pair i as a function of observable socioeconomic characteristics $\mathbf{X}_{ij}$ as well as three unobserved effects. We assume that y_{ij} is a function of an additive genetic effect, a_{ij}, an effect of the environment common to both twins (e.g., parenting), c_i, and an individual-specific effect, e_{ij}, also capturing idiosyncratic measurement error:

$$y_{ij} = f(\mathbf{X}_{ij}, a_{ij}, c_i, e_{ij}). \tag{1}$$

We assume initially that a_{ij}, c_i, and e_{ij} are uncorrelated with one another and across twin pairs and normally distributed with zero means and variances σ_a^2, σ_c^2, and σ_e^2, respectively, so that the total residual variance σ^2 is the sum of the three variance components. We later model gene-environment interactions by allowing a_{ij}, c_i, and e_{ij} to vary with specific, observable experiences or circumstances.

Identifying variation due to a_{ij}, c_i, and e_{ij} separately is possible due to constraints on the covariances. These constraints are motivated by the genetic similarity of twins as well as assumptions of their upbringing and other aspects of their common environment. Consider two twin pairs $i = 1, 2$ with twins $j = 1, 2$ in each pair, where the first is a pair of identical twins and the second is a pair of fraternal twins. The genetic effects are: $a = (a_{11}, a_{12}, a_{21}, a_{22})'$. Analogously, the common and individual-specific environmental effects are: $c = (c_{11}, c_{12}, c_{21}, c_{22})'$ and $e = (e_{11}, e_{12}, e_{21}, e_{22})'$. Identical and fraternal twin pairs differ in their genetic similarity. Identical twins are genetically identical, and the correlation between a_{11} and a_{12} is set to one. Fraternal twins share on average only 50% of their genes, such that the correlation between a_{21} and a_{22} is 0.5. For both identical and fraternal twin pairs, an equal effect of the common environment is assumed. As a result, we use the following covariance matrices:

$$\mathrm{Cov}(a) = \sigma_a^2 \begin{bmatrix} 1 & 1 & 0 & 0 \\ 1 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0.5 \\ 0 & 0 & 0.5 & 1 \end{bmatrix}, \mathrm{Cov}(c) = \sigma_c^2 \begin{bmatrix} 1 & 1 & 0 & 0 \\ 1 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1 \\ 0 & 0 & 1 & 1 \end{bmatrix}, \mathrm{Cov}(e) = \sigma_e^2 \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}.$$

For the measures of investment biases in this study, we assume that f is a linear function:

$$y_{ij} = \beta_0 + \beta \mathbf{X}_{ij} + a_{ij} + c_i + e_{ij}, \tag{2}$$

where β_0 is an intercept term and β measures the effects of the observable socioeconomic characteristics ($\mathbf{X}_{ij}$), e.g., age, education, income and wealth. We use maximum likelihood to estimate the model using Mplus (Muthén and Muthén, 2010). Reported standard errors are bootstrapped with 1,000 repetitions.

Finally, we calculate the variance components A, C, and E. A is the proportion of the total residual variance in an investment bias that is due to an additive genetic factor:

$$A = \frac{\sigma_a^2}{\sigma_a^2 + \sigma_c^2 + \sigma_e^2}$$

The proportions attributable to the common environment (C) and individual-specific environmental effects (E) are computed analogously.

V Results

In this section, we report our main results with respect to the question to which extent investment biases investors exhibit in real-world financial decisions reflect underlying innate predispositions. For comparison with a large number of papers that have studied investment biases, we focus on measures constructed for individual stocks, but also provide results when including mutual funds.

We first compare correlations between genetically identically investors with correlations between related, but genetically non-identical investors. Such a comparison provides intuitive evidence on the importance of latent genetic factors. We then provide formal estimation results from decomposing investment biases into genetic and environmental variation. Finally, we perform a large number of robustness checks.

A Evidence from Correlations

For each investment behavior introduced previously, Figure 1 reports correlations between identical twins as well as same and opposite-sex fraternal twins. We draw several conclusions from the evidence. First, for each measure, we find that the correlation is significantly greater between identical relative to fraternal twins. This difference indicates that to some extent investors display more or less of a given investment bias due to their genetic make-up. On average, the correlation between identical twins is about twice the correlation between fraternal twins. Second, the correlations for same-sex fraternal twins is generally larger than those for opposite-sex twins. This result suggests that gender affects investment behaviors. In our formal model of the origins of investment biases, we will therefore control for gender. In addition, we will provide a robustness check that excludes opposite-sex twins. Finally, we note that the correlation for identical twins is between 25 and 50%, significantly different from one, suggesting that individual-specific experiences and events are also important for the understanding of why investors exhibit investment biases.

B Empirical Decomposition of Investment Biases

We use the model in equation (2) to empirically decompose the variation in investment behaviors across individuals into genetic and environmental components. In Panel A of Table 4, we report results from a model that only controls for gender and age which explain very little of the variation in investment behaviors. Thus, most of the variation remains unexplained. This unexplained variation is decomposed into genetic and environmental components. For each component, we report its relative contribution to the unexplained variation of each investment behavior. A denotes genetic variation, while C and E denote common and individual-specific environmental variation.

The evidence suggests that variation across individual investors with respect to all six investment biases examined reflects to a significant extent genetic differences between investors. Genetic factors seem to be particularly influential in determining *Diversification* and *Home Bias*, where they account for around 45% of the (unexplained) variation. For the remaining behaviors, genetic variation still accounts for between a quarter and a third of the variation. That is, individuals are to a significant extent born with predispositions that later in life and under the conditions typically experienced by an investor in our data set manifest themselves in the investment biases we examine in this paper. The findings also suggest that at least 55% of the variation in investment behaviors is due to environmental factors, represented by the C and E components. Almost all of the environmental variation reflects individual-specific experiences, circumstances, events, and possibly measurement error.[9] The C component is insignificant suggesting that upbringing or other aspects of the common environment do not affect investment biases. That is, the notion that children learn investment biases from their parents is inconsistent with the data.[10]

Wealthier, more educated, and generally more sophisticated investors often make better financial decisions and exhibit fewer investment biases (e.g., Agnew (2006), Dhar and Zhu (2006), Kumar (2009), Calvet et al. (2009)). It is possible that certain frictions, such as transaction costs, are less binding for these investors or that these investors have access to better financial advice. At the same time, they likely have superior cognitive abilities which have also been shown to lower investment biases (Grinblatt et al. (2011, 2012)). Importantly, some of the variation in these characteristics, i.e. wealth, education, and, in particular, IQ is due to genetic differences across investors (see, e.g., Bouchard and McGue (1981), Davies et al. (2011), Behrman and Taubman (1989), and Cronqvist and Siegel (2011)). To rule out that our findings with respect to the genetic origins of behavioral biases reflect genetic variation in these characteristics, we repeat the analysis controlling for several of these socioeconomic characteristics. In particular, in addition to age and gender, we control for education, marital status, wealth, and income.[11] We do not have data on cognitive abilities, but several of the included characteristics, in particular education and wealth, have been shown to be correlated with measures of IQ. The results in Panel B of Table 4 confirm that in particular education and wealth are often associated with lower investment biases. At the same time, the additional controls explain only little of the variation in investment biases, in five out of six cases less than 5%. Decomposing the remaining unexplained variation yields therefore very similar results

[9]Since our data set comes from the Swedish Tax Agency, which in turn obtains the data directly from financial institutions, reporting errors should be relatively rare. To reduce measurement error, we use whenever possible time-series averages (over up to eight years) of annually measured investment behaviors.

[10]The evidence of an insignificant C component is consistent with evidence from behavioral genetics research (e.g., Bouchard et al. (1990)) and recent research on risk preferences (e.g., Barnea, Cronqvist, and Siegel (2010) and Cesarini et al. (2010)).

[11]For the *Disposition Effect*, we also include *Turnover* and the *Number of Holdings* as control (see Dhar and Zhu (2006)).

as in Panel A: Genetic differences remain an important source of variation for all six investment behaviors (still accounting for 25 to 45%), while almost all of the remaining environmental variation is individual-specific.

Our results suggest that future research in genetics as well as in economics and the social sciences in general is needed to understand in detail how investment biases arise and how they can possibly be reduced. While recent studies in molecular genetics, using DNA level data, have confirmed the relative importance of genetic differences first documented using twin studies (Jian et al. (2010) and Davies et al. (2011)), the relative variation that can be explained by linear combinations of specific genes that are associated with the outcome of interest is (still) low, rarely exceeding 10% (Visscher (2008)). This suggests that the latent genetic component that we document for several investment biases likely consists of many genes and possibly their interactions. Interestingly, our results show that first-order socioeconomic characteristics leave most of the observed variation unexplained. This suggests that the environmental factors and mechanisms representing the substantial E component could be similarly complex, possibly consisting of many particular events and circumstances that influence an individual's investment behavior.

Finally, in Table 5, we repeat our analysis for investment behaviors measured across all equity investments, including mutual funds. While much of the existing literature in finance has focused on individual investors' choices with respect to individual stocks, many investors invest in mutual funds as well. It is possible that genetic predispositions are moderated by delegating mainly the selection of specific assets to an outside fund manager. We re-estimate the models previously estimated for stock investments only and find that the relative importance of genetic factors as captured by the A components is lower than what we found for the case of direct stock holdings, but only slightly so. The A component ranges between 16-38%, depending on the investment behavior. We conclude that genetic differences affect preference or belief differences with respect to direct as well as indirect or delegated equity investments.

In the remainder of the paper, we again focus on measures constructed for individual stocks. We also continue to include the socioeconomic controls first introduced in Panel B of Table 4.

C Robustness

We provide several robustness checks regarding sample composition, model misspecification, and model assumptions.

C.1 Opposite-Sex Twins

We noted in Figure 1 that the correlations for same-sex fraternal twins are generally greater than those for opposite-sex twins. A concern is that including opposite-sex twins in our analysis results in an upward bias of the relative importance of genetic factors, as captured by A, as identical twins always have the same sex. As a robustness test, we exclude opposite-sex fraternal twins from our sample and re-estimate the above models. Panel A of Table 6 shows that our results are essentially unaltered compared to the estimates reported in Panel B of Table 4.

C.2 Model Misspecification

Some of the reported C components in Table 4 are exactly zero, reflecting a corner solution as we constrain all variance components to be non-negative. This raises concerns about model misspecification. As a robustness check, we re-estimate the model in equation (2), without non-negativity constraints on the individual variance components. Table 6 Panel B shows that the emerging negative C components are very small in magnitude (-3.9% to -9.8%) and never statistically significant from zero, reducing concerns about misspecification bias.

A related concern is that some of the measures of investment behaviors are censored (e.g., *Home Bias* is between 0 and 1). We have verified that a Tobit model specification results in unchanged, and sometimes stronger, A components (not tabulated).

C.3 Model Assumptions

Equal Environments Assumption (EEA). If parents or others in an individual's environment treat identical twins more similarly than parents or others treat fraternal twins (along dimensions that are relevant for the investment behaviors we study), then A may be upward biased. This is a well-recognized problem in twin research, and as a result substantial resources have been (and continue to be) devoted to tests of the EEA.[12] From research on IQ and personality, where the EEA has to date been tested most rigorously, the evidence suggests that any bias from violations of the EEA is not of first order importance (e.g., Bouchard (1998)). Specifically, researchers have studied twins reared apart, i.e., twins separated at birth or early in life, for which there is no common parental environment. Such studies often produce heritability estimates similar to those using twins who were reared together (e.g., Bouchard et al. (1990)). Perhaps even more convincingly, recent progress has enabled researchers to construct DNA-based measures of pairwise genetic relatedness, which were then related to different outcomes, e.g., height and IQ (Jian et al. (2010) and Davies et al. (2011)). Differently from twin studies, these studies use unrelated subjects and show without relying on any assumptions such as the EEA that at least 50% of the variation in the studied outcomes is due to genetic variation. Finally, specialist twin researchers continue to test the EEA. One concern has been that the matched physical appearance of identical twins result in more similar treatment by those who are a part of these individuals' environments, in the end causing more similar outcomes. Using a clever research design, Segal (2012) studies unrelated look-alike individuals, and finds that their correlations for personality measures are much lower than for identical twins, suggesting that identical twins' similarity mostly reflects similarity in their genes, and not similar treatments by others.

<u>Intra-Twin Pair Communication.</u> If identical twins communicate more with one another than fraternal twins, and if such interaction impacts their investments (e.g., Bikhchandani, Hirshleifer, and Welch (1998) and Hong, Kubik, and Stein (2004)), then A may reflect the direct as well as indirect (via increased communication) effects of genetic similarity. We address this concern using two robustness checks. First, we exclude twin pairs with more than 50% similarity in their portfolios.[13] Panel C of Table 6 reveals evidence of a substantial genetic effect even when excluding twins with similar portfolios. Second, we control directly for intra-twin pair communication. To do so, we sort twin pairs into deciles based on intra-twin pair contact frequency (available for a subset of twins from STR) and randomly exclude twins until we have equally many identical and

[12]See, e.g., Goldberger (1979) for a discussion of common concerns related to twin studies.

[13]Specifically, we drop twin pairs for whom the sum of the absolute value of portfolio weight differences is less than one (on a range between zero for identical portfolios and two for non-overlapping portfolios).

fraternal pairs in each decile. We repeat this process 100 times and then perform one estimation for each of the 100 samples. Table 6 Panel D reports that the median A components are still large and statistically significant. Only for the *Disposition Effect* do we no longer find a significant genetic effect once we control for communication, but the sample size for this specific robustness check is very small contributing to the large confidence interval.

C.4 Relatively Large Portfolios

Investors with relatively small portfolios may not be incentivized to overcome innate predispositions to certain biases. As a robustness check, we therefore exclude all individuals for whom the equity portfolio does not constitute at least 20% of their total assets. The results in Table Panel E of Table 6 suggest that genetic factors continue to be important even among investors with substantial equity exposure.

VI Additional Results

A Behavioral Consistency: Investment Biases and Behaviors in Other Domains

We examine whether some of the previously analyzed investment biases are in fact facets of broader behaviors. Specifically, we identify behaviors in domains other than investments, and then we estimate the genetic correlation between investment biases and those behaviors in other domains. An example is the preference for familiarity. As described in Section II, recent papers study the genetic basis of familiarity (e.g., Chew et al. (2011)). We therefore examine if a preference for the familiar in the investment domain is correlated with a preference for familiarity in some other domains, and most importantly, whether genetic factors influencing the *Home Bias* also affect familiarity preferences in other domains. We consider two measures of familiarity preferences in domains other than investments: the distance between an individual's home location and her birth place, *Distance to Birthplace*, and an indicator for whether an individual's spouse is born in the same region as the individual herself, *Spouse from Home Region*.

In Table 7, we report results from decomposing the covariance of these investment and other behaviors into components corresponding to genetic effects and effects of common and individual-specific environments. Specifically, we use a bivariate Cholesky decomposition (see Neale and Maes (2004) for details). This model controls for individual socioeconomic characteristics such as income and wealth that may determine both investment behavior and non-investment choices.

We report several results. First, variation in familiarity in other, non-investment, domains reflects significant genetic differences: 40% for home location and 15% for choice of spouse. Second, *Home Bias* and *Distance to Birthplace* are significantly negatively correlated, suggesting that those with relatively more local stocks also have a stronger preference for a home location close to their birth place. Finally, and most importantly, the significantly negative genetic correlation between both behaviors suggests that the genetic factors affecting *Home Bias* also affect *Distance to Birthplace*. While we do not find an overall correlation between *Home Bias* and *Spouse from Home Region*, we find a large, though statistically not significant, positive genetic correlation between both behaviors.

This evidence is important because it suggests that behavioral consistency across several domains might be due to genetic endowments. That is, individuals are born with certain predispositions that affect their behaviors in many domains, including investments. The finding is also consistent with the view that preferences or behavior reflect psychological mechanisms that have been shaped by evolutionary forces whose effects extend to choices, such as financial investment decisions, that did not exist in ancient times.

B Moderators of Genetic Effects of Investment Biases

Our main results in Table 4 suggest that, depending on the specific investment behavior, genetic variation accounts for 25 to 45% of the variation across individuals. It is important to note that the relative importance of genetic relative to non-genetic factors can vary across different investors or environments. Cunha and Heckman (2010) go as far as concluding that "the nature versus nurture distinction is obsolete" (p. 3), and they argue that the notion that genes are moderated by environments should receive more attention in economic research. For an extensive review of research on so called "gene-environment interactions", we refer to Rutter (2006).

B.1 Work Experience in Finance

Does work experience in a corporate treasury department or in the finance industry reduce the impact of genetic predispositions with respect to investment biases? We use data on an individual's occupation, based on the International Standard Classification of Occupations (ISCO-88) by the International Labour Organization (ILO) and available for a subset of our sample, to identify twins with work experience related to finance. We re-estimate the above models including only twins with relevant finance experience. To increase the sample size we consider direct as well as indirect holdings of equity. We include the same socioeconomic controls as previously.

Table 8 reports the corresponding results. For twins with financial experience, the relative importance of genetic factors is substantially smaller for each of the investment behaviors than in case of the general population (see Table 5).[14] Only for *Skewness Preference* does the A component remain marginally significant at 15%. For *Diversification*, *Home Bias*, and *Performance Chasing*, genetic differences seem to account for almost none of the variation. For *Turnover*, the A share decreases to 10% and is no longer statistically significant. At the same time, the similar work environment experienced by this specific subset of twins generates pair-specific commonality in their behavior.

While we cannot rule out that the selection into specific occupations reduces the relevant genetic variation in this particular sub-sample, the evidence in Table 8 is certainly consistent with work experience with finance reducing the impact of genetic predispositions with respect to investment biases.

B.2 General Education

Education is a potentially important moderator of genetic effects. For example, Johnson et al. (2010) report, in a different context, that education reduces expressions of genetic predispositions to poor health. Individuals may be born with a propensity to poor health, but education enables them to reduce such genetic propensities. In our paper, it is therefore interesting to examine the extent to which education moderates the importance of genetic factors for investment biases.

[14] We have too few twin pairs with occupational financial experience to estimate a separate model for *Disposition Effect*.

In terms of empirical methodology, we rely on the gene-environment interaction model by Purcell (2002). Figure 2 provides a graphical description of the model. In contrast with the model outlined in equation (2), a moderator (M), here education, interacts with the unobservable genetic and environmental factors of the investment behavior (y). The model allows education and the investment behavior to be correlated via exposure of the investment behavior to the unobservable genetic and environmental factors of the moderator. That is, we include all twins with non-missing education data and account for the possibility that educational outcomes and investment behaviors are not independent. Finally, we use regressions to remove the effect of the socioeconomic characteristics used as control variables in Table 4, with the exception of educational characteristics (not tabulated).

We measure educational outcome with *Years of Education* which is based on the highest completed degree.[15] To reduce the dimensionality of the analysis, we employ the previously introduced *Investment Bias Index* that summarizes the six investment behaviors for each individual.

Figure 3 reports a graphical summary of the results, displaying the absolute size of the genetic and environmental variances (vertical axis) as a function of *Years of Education* (horizontal axis). We find that education does not reduce the effect of genetic predisposition to investment biases. In particular, the detailed results of the model estimation in Appendix Table A2 suggest a small increase in genetic variance due to education.[16] Further, Figure 3 shows that the variance of common environmental effects also increases slightly, but in a statistically insignificant way, as individuals obtain more education, while the individual-specific environmental variation remains unchanged.

These results suggest that differences in genetic propensity to certain investment biases do not decrease with an increase in general educational achievement. Importantly, while professional finance experience seems to reduce genetic propensities to investment biases, general education does not seem to have a similar effect.

[15] For some individuals, we have information on their highest degree, but not on *Years of Education*. We use a linear regression model to estimate *Years of Education* for those individuals. See Appendix Table A1 for details.

[16] This conclusion is based on a significantly positive estimate of $alpha\_u$ which has the same sign as the estimate of a_u. For estimation purposes, *Years of Education* is expressed in units of 10 years.

C Evidence from Discordant Twin Pair Research Design

While our results demonstrate the important role genetic factors play in determining investment behaviors, they also show that substantial variation observed among the individuals in our sample is due to individual-specific environmental effects, captured by the E component in our variance decomposition results. Identifying the specific circumstances, experiences, or events as well as the mechanisms through which they impact investment choices is important for better models of investor behavior as well as public policy. Given that differences in education, net-worth, and income explain typically less than 10% of the total variation, substantial work seems to be left for social scientists. One particular challenge researchers face when trying to identify causal effects of specific environmental conditions is that individuals have been shown to self-select into experiences and even life events partly as a function of their genetic predispositions. Consequently, controlling for genetic factors is important in the search of environmental factors that matter for investment behaviors. Using the socioeconomic variables included in our model, we show how genetically informed data, such as twin data, can be used to address such confounding effects.

Using data on identical twins allows us to apply a "discordant twin-pair research design" that approximates a natural experiment. The approach allows to compare the investment behaviors of twin pairs who are discordant on, e.g., education, but match on genes and shared environment. The design provides a useful analogue to a counterfactual design, and the absence of an association within discordant twin pairs means that a previously observed association between an individual characteristic and investment behavior is attributable to common genetic or shared environmental factors.

We select all identical twins from our sample of twins with direct stock holdings. We observe that about 20% of them are discordant with respect to their education. We use a standard linear regression model to regress *Investment Bias Index* on a set of socioeconomic characteristics, including education. The first column in Table 9 reports results. One of the important results is that college degree is significantly inversely related to investment biases.

In the second column, we report evidence from a discordant twin pair research design for a pair

i of identical twins ($j = 1, 2$) that were reared together.[17] If an investment bias y_{ij} is linear in observable socioeconomic characteristics and unobservable genetic and environmental effects, a_i, c_i, and e_{ij}, we can eliminate the genetic and shared environmental effects, a_i and c_i, by considering the difference between the twins in a pair:

$$y_{ij} = \beta_0 + \beta \mathbf{X}_{ij} + a_i + c_i + e_{ij} \tag{3}$$

$$y_{i1} - y_{i2} = \beta(\mathbf{X}_{i1} - \mathbf{X}_{i2}) + e_{i1} - e_{i2}\ . \tag{4}$$

Comparing the estimates in the first and second columns, we conclude that the effects of a college degree is reduced once we eliminate genetic and shared environmental effects. That is, the effects of college degree on investment biases reported in the first column are confounded, and attributable to unobservable genetic or shared environmental factors.

The specific result with respect to education suggests that general education, as measured by a college degree, does not cause a reduction in investment biases. This result does not suggest that more targeted financial literacy initiatives cannot affect individuals' investment choices. More generally, though, the evidence presented here suggests that genetically informed data can play an important role when evaluating the causal effect of circumstances, experiences, or events with respect to investment behavior.

VII Conclusion

In this paper, we have examined the following question: Why do individuals exhibit investment biases? Our focus in this paper has been on the relative importance of genetic and environmental factors. For a long list of well-recognized investment biases (e.g., the reluctance to realize losses, performance chasing, and the home bias), we find that genetic factors explain up to 45% of the variation across individual investors. But the relative importance of genetic relative to environmental factors is found to vary substantially across different investors. For example, among investors with work experience in finance, we find a significant reduction of the relative amount of genetic variation,

[17] See Taubman (1976) for an early application of this empirical methodology.

which is consistent with practical experience in finance moderating genetic predispositions to investment biases. Interestingly, we do not find that general education has a similar moderating effect.

These results have implications for the design of public policy in the domain of financial literacy (e.g., Lusardi and Mitchell (2007) and Van Rooij, Lusardi, and Alessie (2011)). Specifically, the findings suggest that policy should be designed considering the existence of genetic predispositions as well as the potential difficulties in reducing those predispositions through general education. Recent research has reached similar conclusions. For example, Bhattacharya et al. (2012) show in a large field study that investors who are offered unbiased investment advice often are not interested in the advice and even those that are interested rarely follow the advice.

Our evidence is consistent with evolutionary arguments of behavior as in Rayo and Becker (2007) and Brennan and Lo (2011). Nature selects fitness maximizing behaviors, i.e., behaviors associated with a reproductive advantage relative to alternative behaviors. What in finance research is referred to as "biases" may indeed be manifestations of fitness maximizing psychological mechanisms. Consistent with this view of investment biases as partly innate features of human behavior, we find that the genetic factors that influence investment biases also affect behaviors in other, non-investment, domains.

So what explains the genetic effects we find? As argued in Table 1 of our paper, recent research in behavioral genetics has linked specific genes to several of the psychological mechanisms that may manifest themselves as investment biases. That is, some individuals are endowed with genes linked to overconfidence, sensation seeking, or loss aversion, and these genes may manifest themselves in the individual's investment behavior, as well as in the individual's behavior in non-investment domains. An additional explanation, which is consistent with recent work in finance (e.g., Grinblatt, Keloharju, and Linnainmaa (2011, 2012)), is that IQ is genetic, which results in genetic variation in investment biases.

While a significant portion of our paper emphasizes genetic predispositions to investment biases, it is important to also recognize that the environment an investor experiences also affects investment biases, either as a moderator of genetic predispositions or directly. Indeed, more than 50% of the variation in investment biases across investors is attributable to individual-specific experiences and events. We encourage future research in this field to dig deeper into which specific individual experiences (e.g., early in an individual's life or career) are most important when it comes to shaping investment behavior.

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Table 1
The Genetic Basis of Investment Biases

Investment behavior	Psychological mechanism(s)	Gene(s)	Empirical evidence
Insufficient diversification	Ambiguity aversion	DRD5 (microsatellite marker); ESR2 (CA repeat)	Chew et al. (2011)
	Familiarity	SLC6A4 (5-HTTLPR indel)	Chew et al. (2011)
Excessive trading	Overconfidence		Twin study design: Cesarini et al. (2009)
	Sensation seeking	Multiple SNPs in 4 dopamine genes	Derringer et al. (2010)
			Twin study design: Fulker et al. (1980)
Disposition effect	Prospect theory	9-repeat vs. 10-repeat allele of DAT1	Zhong et al. (2009)
		10-repeat vs. 12-repeat allele of STin2	Zhong et al. (2009)
			Loss aversion in Capuchin monkeys (Chen et al. (2006))
	Mental accounting / Framing		Narrow framing in Capuchin monkeys (Lakshminarayanan et al. (2011))
			Twin study design: Cesarini et al. (2012)
Performance chasing	Excessive extrapolation		
	Hot hands fallacy		
Skewness preference	Cumulative prospect theory	Monoamine oxidase A (4 repeat)	Zhong et al. (2009)
			Twin study design: Slutske et al. (2000)

Table 1 provides information on existing evidence from behavioral genetics with respect to investment behaviors examined in this paper.

Table 2
Summary Statistics

Panel A: Number of Twins by Zygosity and Gender

	All Twins	Identical Twins			Fraternal Twins			
		Male	Female	Total	Same Sex: Male	Same Sex: Female	Opposite Sex	Total
Number of twins (*N*)	30,416	4,066	5,206	9,272	4,522	5,326	11,296	21,144
Fraction (%)	100%	13%	17%	30%	15%	18%	37%	70%

Panel B: Socioeconomic Characteristics and Equity Portfolio Characteristics

	All Twins	Identical Twins			Fraternal Twins		
Variable	*N*	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.
Age	30,416	47.08	48.00	17.64	53.06	55.00	15.51
Less than High School	30,416	0.15	0.00	0.35	0.20	0.00	0.40
High School	30,416	0.22	0.00	0.41	0.26	0.00	0.44
College or more	30,416	0.58	1.00	0.49	0.47	0.00	0.50
No Education Data available	30,416	0.06	0.00	0.23	0.06	0.00	0.24
Married	30,416	0.46	0.00	0.50	0.54	1.00	0.50
Disposable Income (USD)	30,416	31,379	25,476	27,592	35,203	27,678	35,449
Financial Assets (USD)	30,416	40,759	14,537	155,296	48,062	17,342	442,298
Total Assets (USD)	30,416	124,351	71,883	252,478	142,603	83,504	576,198
Total Debt (USD)	30,416	31,802	16,020	68,330	30,396	13,759	149,778
Net Worth (USD)	30,416	92,549	42,961	223,277	112,207	56,417	516,665
Number of Stocks and Equity Mutual Funds	30,416	3.56	2.33	3.80	3.62	2.25	3.97
Value of Stocks and Equity Mutual Funds (USD)	30,416	16,841	3,662	109,292	24,815	4,159	663,773
Number of Stocks	12,378	3.32	1.89	3.91	3.42	1.89	4.15
Value of Stocks (USD)	12,378	22,558	2,825	163,360	29,218	2,819	543,596
Number of Equity Mutual Funds	23,870	2.41	1.89	1.84	2.34	1.80	1.86
Value of Equity Mutual Funds (USD)	23,870	7,018	2,059	20,160	7,788	2,292	17,304

Table 2 Panel A provides information on the number of identical and non-identical twins used in this study. Panel B provides summary statistics for several socioeconomic characteristics and portfolio characteristics, separately for identical and non-identical twins. All variables are defined in detail in Appendix Table A1.

Table 3
Investment Behaviors

	All Twins	Identical Twins			Fraternal Twins		
	N	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.
Stocks							
Diversification	12,378	3.32	1.89	3.91	3.42	1.89	4.15
Home Bias	12,378	0.94	1.00	0.16	0.94	1.00	0.15
Turnover	11,508	0.20	0.03	0.35	0.17	0.02	0.33
Disposition Effect	782	0.04	0.00	0.38	0.05	0.00	0.47
Performance Chasing	6,672	0.15	0.00	0.22	0.14	0.00	0.22
Skewness Preference	12,378	0.04	0.00	0.10	0.03	0.00	0.10
Investment Bias Index	12,378	4.67	5.00	1.49	4.58	5.00	1.43
Stocks and Equity Mutual Funds							
Diversification	30,416	0.70	0.93	0.38	0.67	0.89	0.39
Home Bias	30,416	0.51	0.47	0.30	0.53	0.49	0.31
Turnover	28,108	0.27	0.17	0.38	0.25	0.14	0.37
Disposition Effect	3,086	0.02	0.00	0.43	0.02	0.00	0.43
Performance Chasing	25,530	0.10	0.00	0.16	0.10	0.00	0.16
Skewness Preference	30,416	0.05	0.00	0.10	0.06	0.00	0.10

Table 3 reports summary statistics for the main measures of investment behavior, *Diversification*, *Home Bias*, *Turnover, Disposition Effect*, *Performance Chasing*, and *Skewness Preference* as well as the *Investment Bias Index*. *Diversification* and *Turnover* are measured differently for stocks and stocks and equity mutual funds. See Appendix Table A1 for a detailed definition of all variables.

Table 4
Decomposition of Investment Behaviors

Panel A: Controlling for Gender and Age

	Diver-sification	Home Bias	Turnover	Disposition Effect	Performance Chasing	Skewness Preference
Intercept	1.916	0.912	0.152	-0.146	0.126	0.012
	0.344	0.017	0.031	0.161	0.030	0.008
Male	0.553	0.011	0.078	-0.038	0.026	0.012
	0.074	0.003	0.006	0.034	0.005	0.002
Age	0.220	0.010	0.017	0.098	0.012	0.013
	0.151	0.007	0.012	0.064	0.012	0.003
Age - squared	0.001	-0.001	-0.003	-0.010	-0.002	-0.002
	0.016	0.001	0.001	0.006	0.001	0.000
Fraction of Unexplained Variance	0.992	0.990	0.977	1.000	0.989	1.000
A Share	0.437	0.456	0.254	0.294	0.303	0.279
	0.099	0.053	0.027	0.135	0.091	0.051
C Share	0.091	0.000	0.000	0.000	0.102	0.000
	0.066	0.028	0.000	0.057	0.066	0.029
E Share	0.471	0.544	0.746	0.706	0.595	0.721
	0.043	0.037	0.027	0.105	0.038	0.034
N	12,378	12,378	11,508	782	6,672	12,378

Table 4 (continued)

Panel B: Controlling for Socioeconomic Characteristics

	Diver-sification	Home Bias	Turnover	Disposition Effect	Performance Chasing	Skewness Preference
Intercept	-7.780	0.938	-0.265	-0.482	0.014	-0.095
	1.216	0.035	0.073	0.384	0.060	0.024
Male	0.210	0.013	0.076	-0.055	0.024	0.010
	0.068	0.003	0.006	0.036	0.006	0.002
Age	-0.698	0.016	0.025	0.098	0.015	0.013
	0.151	0.007	0.013	0.067	0.013	0.003
Age - squared	0.053	-0.001	-0.004	-0.010	-0.003	-0.002
	0.015	0.001	0.001	0.006	0.001	0.000
High School	0.116	0.001	0.021	0.000	-0.016	-0.001
	0.105	0.004	0.010	0.061	0.010	0.003
College or More	0.512	-0.013	0.029	-0.068	-0.027	0.001
	0.113	0.004	0.009	0.045	0.009	0.003
No Education Data Available	0.027	-0.008	0.009	-0.080	-0.015	0.005
	0.081	0.003	0.007	0.034	0.007	0.002
Married	-0.086	-0.002	-0.005	-0.017	-0.013	0.003
	0.087	0.003	0.008	0.038	0.007	0.002
Second Net Worth Quartile Indicator	0.458	-0.006	-0.031	-0.052	0.006	-0.003
	0.060	0.004	0.010	0.067	0.009	0.003
Third Net Worth Quartile Indicator	0.979	-0.014	-0.051	-0.029	0.003	-0.008
	0.080	0.004	0.010	0.069	0.010	0.003
Highest Net Worth Quartile Indicator	2.862	-0.026	-0.055	-0.042	-0.006	-0.010
	0.108	0.004	0.010	0.065	0.009	0.003
Log of Disposable Income	0.939	-0.002	0.033	0.039	0.012	0.009
	0.111	0.002	0.006	0.033	0.005	0.002
Turnover (Sales)				0.008		
				0.008		
Number of Holdings				-0.003		
				0.002		
Fraction of Unexplained Variance	0.868	0.990	0.969	0.979	0.989	0.967
A Share	0.453	0.452	0.251	0.272	0.311	0.275
	0.084	0.053	0.029	0.127	0.091	0.050
C Share	0.030	0.000	0.000	0.000	0.095	0.000
	0.052	0.028	0.007	0.045	0.065	0.028
E Share	0.516	0.548	0.749	0.728	0.594	0.725
	0.042	0.037	0.027	0.109	0.039	0.034
N	12,378	12,378	11,508	782	6,672	12,378

Table 4 reports results from maximum likelihood estimation. The different investment behaviors are modeled as linear functions of observable socioeconomic variables and random effects representing additive genetic effects (A), shared environmental effects (C), as well as an individual-specific error (E). For each estimated model, we report the coefficient estimates for the socioeconomic variables, the *Fraction of Variance Unexplained*, i. e. the amount of total variation that cannot be explained by the observable independent variables, and the fraction of this unexplained variance that is due to unobserved genetic and environmental effects (*A* Share – for the additive genetic effect, *C* Share – for common environmental effect, *E* Share – for the individual-specific environmental effect) as well as the corresponding bootstrapped standard errors (1,000 resamples). Only direct stock holdings are considered in the measurement of the different investment behaviors. Panel A and B differ only with respect to the included control variables. All variables are defined in Appendix Table A1. *N* provides the number of observations used in each estimation.

Table 5
Stocks and Mutual Funds

		Variance Components		
Model	*N*	*A* - Share	*C* - Share	*E* - Share
Diversification	30,416	0.379	0.020	0.601
		0.032	0.021	0.015
Home Bias	30,416	0.345	0.000	0.655
		0.012	0.002	0.012
Turnover	28,108	0.251	0.000	0.749
		0.022	0.008	0.018
Disposition Effect	3,086	0.160	0.000	0.840
		0.053	0.021	0.045
Performance Chasing	25,530	0.267	0.000	0.733
		0.019	0.003	0.019
Skewness Preference	30,416	0.266	0.000	0.734
		0.036	0.017	0.024

Table 5 reports results from maximum likelihood estimation. The different investment behaviors are modeled as linear functions of observable socioeconomic variables (see Table 4 for a list of the variables included) and unobservable random effects representing additive genetic effects (A), shared environmental effects (C), as well as an individual-specific error (E). For each estimated model, we report the variance fraction of the combined error term explained by each unobserved effect (*A* Share – for the additive genetic effect, *C* Share – for common environmental effect, *E* Share – for the individual-specific environmental effect) as well as the corresponding bootstrapped standard errors (1,000 resamples). Investment behaviors are derived from all holdings of stocks as well as equity mutual funds. All variables are defined in Appendix Table A1. *N* provides the number of observations used in each estimation.

Table 6
Robustness Checks

Panel A: Opposite-Sex Twins

Model	*N*	Variance Components *A* - Share	*C* - Share	*E* - Share
Diversification	7,916	0.379	0.083	0.538
		0.111	0.084	0.044
Home Bias	7,916	0.459	0.013	0.528
		0.086	0.063	0.041
Turnover	7,412	0.270	0.000	0.730
		0.053	0.033	0.032
Disposition Effect	564	0.245	0.000	0.755
		0.135	0.043	0.120
Performance Chasing	4,390	0.331	0.085	0.584
		0.102	0.079	0.040
Skewness Preference	7,916	0.282	0.000	0.718
		0.057	0.037	0.036

Panel B: Model Misspecification

Model	*N*	Variance Components *A* - Share	*C* - Share	*E* - Share
Home Bias	12,378	0.505	-0.044	0.539
		0.102	0.072	0.042
Turnover	11,508	0.356	-0.082	0.726
		0.077	0.051	0.033
Disposition Effect	782	0.411	-0.098	0.688
		0.292	0.180	0.136
Skewness Preference	12,378	0.325	-0.039	0.714
		0.101	0.070	0.041

Table 6 (continued)

Panel C: Excluding Similar Portfolios

Model	*N*	Variance Components		
		A - Share	*C* - Share	*E* - Share
Diversification	9,902	0.327	0.015	0.658
		0.078	0.049	0.042
Home Bias	9,902	0.236	0.000	0.764
		0.061	0.028	0.043
Turnover	8,990	0.208	0.000	0.792
		0.044	0.021	0.033
Disposition Effect	582	0.155	0.000	0.845
		0.116	0.048	0.103
Performance Chasing	5,208	0.201	0.060	0.739
		0.087	0.060	0.040
Skewness Preference	9,902	0.111	0.054	0.835
		0.067	0.051	0.031

Panel D: Controlling for Differences in Intra-Twin Pair Communication

Model	*N*	Variance Components		
		A - Share	*C* - Share	*E* - Share
Diversification	6,228	0.251	0.176	0.578
		0.130 - 0.369	0.073 - 0.282	0.544 - 0.598
Home Bias	6,228	0.216	0.209	0.574
		0.130 - 0.360	0.090 - 0.292	0.547 - 0.604
Turnover	5,836	0.241	0.020	0.744
		0.136 - 0.272	0.000 - 0.108	0.725 - 0.764
Disposition Effect	412	0.177	0.000	0.805
		0.000 - 0.297	0.000 - 0.080	0.702 - 0.953
Performance Chasing	3,544	0.224	0.164	0.612
		0.131 - 0.315	0.089 - 0.251	0.586 - 0.638
Skewness Preference	6,228	0.209	0.071	0.723
		0.080 - 0.290	0.000 - 0.179	0.694 - 0.757

Table 6 (continued)

Panel E: Investors with at Least 20% of Total Assets Invested in Risky Financial Assets

Model	*N*	Variance Components *A* - Share	 *C* - Share	 *E* - Share
Diversification	2,574	0.656	0.000	0.344
		0.089	0.052	0.053
Home Bias	2,574	0.499	0.134	0.367
		0.174	0.127	0.073
Turnover	2,306	0.438	0.000	0.562
		0.143	0.078	0.089
Disposition Effect	344	0.227	0.000	0.773
		0.214	0.076	0.192
Disposition Effect (LA70)	862	0.452	0.000	0.548
		0.102	0.047	0.084
Performance Chasing	1,814	0.297	0.224	0.479
		0.171	0.133	0.068
Skewness Preference	2,574	0.350	0.040	0.609
		0.163	0.126	0.082

Table 6 reports results from maximum likelihood estimation for investment behaviors measured on direct stock holdings only. The different investment behaviors are modeled as linear functions of observable socioeconomic variables (see Table 4 for a list of the variables included) and unobservable random effects representing additive genetic effects (A), shared environmental effects (C), as well as an individual-specific error (E). For each estimated model, we report the variance fraction of the combined error term explained by each unobserved effect (*A* Share – for the additive genetic effect, *C* Share – for common environmental effect, *E* Share – for the individual-specific environmental effect) as well as (except for Panel D) the corresponding bootstrapped standard errors (1,000 resamples). Panel A presents results for the subset of twin pairs that exclude opposite-sex twin pairs. Panel B allows the variance components to take on negative values for cases where the shared environmental component (C) is estimated to be zero in Table 4. Panel C reports results for the subset of twin pairs for whom the sum of the absolute value of portfolio weight differences is at least one (on a range between zero (identical portfolios) and two (non-overlapping portfolios). In Panel D, twin pairs are sorted into ten bins based on contact frequency between them (contact frequency ranges from zero to 360 contacts per year). By randomly dropping identical or fraternal twins, we ensure that each bin has the same number of identical and fraternal twin pairs. We repeat the random selection 100 times and report the median as well as the 5th and 95th percentile of the estimated variance fractions. Panel E reports results for the subsample of investors who invest at least 20% of their total assets in risky financial assets. All variables are defined in Appendix Table A1. *N* provides the number of observations used in each estimation.

Table 7

Behavioral Consistency: Investment Biases and Behaviors in Other Domains

	Model I		Model II	
	Home Bias	Distance to Birthplace	Home Bias	Spouse from Home Region
A - Share	0.453	0.400	0.356	0.148
	0.059	0.081	0.111	0.089
C - Share	0.000	0.211	0.000	0.191
	0.038	0.056	0.071	0.066
E - Share	0.547	0.389	0.644	0.661
	0.036	0.036	0.073	0.040
Correlation	-0.027		0.003	
	0.009		0.021	
Genetic Correlation	-0.101		0.221	
	0.034		0.247	
Correlation of Common Environment	0.000		0.000	
Correlation of Individual Environment	0.035		-0.073	
	0.021		0.035	
N	12,180		2,566	

Table 7 reports results from maximum likelihood estimation of a bivariate models. *Home Bias* (measured for direct holdings of stocks) and *Distance to Birthplace* (Model I) or *Spouse from Home Region* (Model II) are modeled jointly as a linear function of observable socioeconomic characteristics (*Home Bias* only - see Table 4 for a list of socioeconomic variables included) as well as three unobservable random effects representing additive genetic effects (*A*), shared environmental effects (*C*), as well as an individual-specific error (*E*). For each model, we report the variance fraction explained by each random effect (*A* Share – for the additive genetic effects, *C* Share – for shared environmental effects, *E* Share – for the individual-specific random effect), the overall correlation between both variables in a given model as well as the correlation between the genetic and individual specific environmental effects of each variable. Corresponding standard errors are bootstrapped with 1,000 resamples. Whenever one of the random effects (A, *C*, or *E*) is estimated to be zero, the corresponding correlation is set to zero. All variables are defined in Appendix Table A1. *N* provides the number of observations used in each estimation.

Table 8
Work-related Experience with Finance

Model	*N*	*A* - Share	*C* - Share	*E* - Share
		Variance Components		
Diversification	622	0.017	0.188	0.795
		0.114	0.090	0.074
Home Bias	622	0.000	0.197	0.803
		0.080	0.078	0.071
Turnover	582	0.108	0.022	0.871
		0.096	0.060	0.083
Performance Chasing	562	0.000	0.086	0.914
		0.092	0.053	0.084
Skewness Preference	622	0.152	0.000	0.848
		0.083	0.018	0.081

Table 8 reports results from maximum likelihood estimation for subsets of twins that have occupational experience in finance. The different investment behaviors are modeled as linear functions of observable socioeconomic variables (see Table 4 for a list of the variables included) and unobservable random effects representing additive genetic effects (A), shared environmental effects (C), as well as an individual-specific error (E). The variance fraction of the combined error term explained by each unobserved effect (*A* Share – for the additive genetic effect, *C* Share – for common environmental effect, *E* Share – for the individual-specific environmental effect) as well as the corresponding bootstrapped standard errors (1,000 resamples).Investment behaviors are derived from all holdings of stocks and equity mutual funds. All variables are defined in Appendix Table A1. *N* provides the number of observations used in each estimation.

Table 9
Discordant Identical Twins: Investment Bias Index

	Level	Twin Differences
Intercept	4.607	-0.026
	0.626	0.035
Male	0.243	
	0.054	
Age	0.175	
	0.112	
Age - squared	0.000	
	0.000	
High School	0.017	0.183
	0.078	0.115
College or More	-0.307	0.057
	0.074	0.123
No Education Data Available	-0.019	0.406
	0.156	0.247
Married	-0.093	-0.040
	0.054	0.067
Above Median Wealth Indicator	-0.640	-0.418
	0.056	0.072
Log of Disposable Income	0.035	-0.040
	0.052	0.071
R^2	0.087	0.021
N	3,952	1,976

Table 9 reports results from linear regressions of the Bias Index (column Level) and the intra twin-pair difference in the Bias Index (column Twin Difference) onto socioeconomic variables. For each estimated model, we report the coefficient estimates as well as the corresponding standard errors. Standard errors are robust to heteroscedasticity as well as correlation between twins in a twin pair. Only direct stock holdings are considered in the construction of the Bias Index. All variables are defined in Appendix Table A1. R^2 is the fraction of total variation explained by the socio-economic variables. N provides the number of observations used in each estimation.

Appendix Table A1
Definition of all Variables

Variable	Description
Types of Twins	
Identical Twins	Twins that are genetically identical, also called monozygotic twins. Zygosity is determined by the Swedish Twin Registry based on questions about intrapair similarities in childhood.
Non-identical Twins	Twins that share on average 50% of their genes, also called dizygotic or fraternal twins. Non-identical twins can be of the same sex or of opposite sex. Zygosity is determined by the Swedish Twin Registry based on questions about intrapair similarities in childhood.
Investment Biases & Trading Behavior	
Diversification	For direct stock holdings, Diversification is defined as the number of distinct stocks held in an individual's portfolio at the end of a year. For holdings of stocks and mutual funds, Diversification is defined as the proportion invested in mutual funds, but not invested in individual stocks. To reduce measurement error, we calculate the equally weighted average Diversification across all years the individual is in the data set.
Home Bias	Home Bias is defined as the equity portfolio share of Swedish securities.In particular, at the end of each year and for each investor, we add the market value of all Swedish stocks in the investor's portfolio to the market value of the Swedish equity allocation of all mutual funds held by the investor. We divide the value of these Swedish equity holdings by the total market value of direct (i.e. stocks) and indirect (i.e. equity allocation of mutual funds) equity holdings. We classify stocks as Swedish or foreign based on the country in which the stock is legally registered, as reflected in the country code of a given stock's ISIN. For mutual funds, we collect annual fund-specific data from Morningstar on the fund's total equity allocation as well as on the fund's equity allocation to Sweden. For equity or mixed mutual funds that are not covered by Morningstar we infer the fund's investment focus from the fund's name. By default, we assume that the fund is fully invested in international equities. Only if the fund name suggests an investment focus on Swedish equity, we classify the fund as Swedish. Finally, to improve the precision of our measure, for each investor we calculate the equally weighted average Home Bias across all years with non-missing data.
Turnover	For direct stock holdings, we divide, for each individual investor and year, the sales volume (in Swedish krona) during the year by the value of directly held stocks at the beginning of the year. Since we do not have sales price information for mutual funds, we also construct a turnover measure using the number of sales during the year divided by the number of equity securities in the investor's portfolio at the beginning of the year. In each case, Turnover is defined as the average annual turnover using all years with equity holdings data for an investor. To avoid that our analysis is affected by outliers, we drop observations for which Turnover is higher than the top one percentile of the Turnover distribution.
Disposition Effect	We measure the Disposition Effect as the difference between the ratio of the number of realized to realized and unrealized gains and the ratio of the number of realized to realized and unrealized losses (see Odean (1998) and Dhar and Zhou (2006)). We do not observe purchases of securities and even though we have data on sales transactions, we do not observe the date of the transaction. We therefore use changes in the annual holding data to identify net purchases and sales of equity securities for each investor. We start by dropping all securities that are present in an investor's portfolio in 1998, the beginning of our sample period, as we cannot observe when the security entered the investor's portfolio. Next, when we observe a given security for the first time in an investor's portfolio at the end of the year, we assign the average (tax) value (averaged between the (tax) value of the previous and the current year) as the relevant purchase and reference price. We increase (decrease) this reference price when additional units of this security are purchased at a higher (lower) value in later years. At the end of each year with at least one sales transaction in the relevant group of securities (stocks or stocks and equity mutual funds), we compare the reference price of each security in an investor's portfolio (including those securities whose holdings decrease to zero over that year) to the currrent value of the security (where the current value is the average of the (tax) value of the previous and the current year). If the current value is higher (lower) than the reference price, we consider the position a gain (loss). We further categorize gains and losses as realized if the number of units held decreases relative to the previous year, and unrealized otherwise. Finally, for each investor, we count the total number of realized and unrealized gains and losses. The Disposition Effect is then the difference between the ratio of realized to realized and unrealized gains and the ratio of realized to realized and unrealized losses. It is set to missing unless both ratios exist.
Performance Chasing	Performance Chasing is measured by an individual's propensity to purchase securities that have performed well in the recent past. Specifically, each year we sort stocks and equity mutual funds separately into return deciles using the raw returns during the year. For each investor and year, we calculate the fraction of purchased securities (identified by positive net-changes of annual holdings) with returns in the top two deciles. Performance Chacing is the average of this fraction over all years in which an investor has made net-purchases of securities.
Skewness Preference	Skewness Preference is measured in the spirit of Kumar (2009). For each investor and year we calculate the fraction of the portfolio that is invested in ``lottery'' securities. We define a security as a lottery security if it has a below median price as well as above median idiosyncratic volatility and skewness. We use a the world market return, the squared world market return, the local Swedish market return, and the squared local market returns factor in our asset pricing model to determine a security's idiosyncratic error term. Regressions are performed every year using the last 24 months of return data. Skewness Preference is the fraction of lottery securities held in an investor's equity portfolio, averaged over all years with portfolio data.

Variable	Description
Investment Bias Index	The Investment Bias Index summarizes the magnitude of the six investment behaviors for direct stock holdings. It takes on values between zero and twelve. For each behavior, we assign a value of zero (no bias), one, or two (most biased), depending on the observed level. The index is the sum across all six investment behaviors. If for a given investor, a behavior is missing, we use the median behavior to assign the bias index component (zero, one, or two). In particular, for Diversification, we assign two to investors with only one stock, one to investors with two to six stocks, and zero to investors with more than six stocks. For Home Bias, we assign two to investors with a 100% allocation to Swedish stocks, one to investors with less than 100%, but more than 20% allocation to Swedish stocks, and zero for investors with less than 20% Swedish allocation. For Turnover, we assign two to investors with a value above 55%, one to investors with a value between 20% and 55%, and zero otherwise. For Disposition Effect, we assign two to investors with a disposition effect over 40%, one to investors with a strictly positive disposition effect, and zero otherwise. For Performance Chasing, we assign two to investors with a value above 40%, one to investors with a value between 20 and 40%, and zero otherwise. For Skewness preference, we assign two to investors with a value above 15%, one to investors with a value between 5 and 15%, and zero otherwise.
Socioeconomic Characteristics	
Male	An indicator variable that equals one if an individual is male and zero otherwise. Gender is obtained from Statistics Sweden.
Age	The average age over the years an individual is included in our sample. Age is obtained from the Statistics Sweden.
Less than High School	An indicator variable that equals one if an individual has not completed high school (gymnsasium) zero otherwise. Educational information is obtained from Statistics Sweden.
High School	An indicator variable that equals one if an individual has completed high school (gymnasium) but has not attended university, zero otherwise. Educational information is obtained from Statistics Sweden.
College or more	An indicator variable that equals one if an individual has attended university, zero otherwise. Educational information is obtained from Statistics Sweden.
No Education data available	An indicator variable that equals one if no educational data are available for an individual, zero otherwise. Educational information is obtained from Statistics Sweden.
Years of Education	Years of Education is based on the highest completed degree. For a subset of the sample, the variable is obtained from the Swedish Twin Registry. We use a linear regression model to extend the variable to the rest of our sample. Specifically, we regress the years of education onto indicator variables High School and College or More (avaialable for most individuals in our data set from Statistics Sweden) and then predict years of education out of sample.
Married	The average (over the years an individual is included in our sample) of an annual indicator variable that equals one if an individual is married in a given year and zero otherwise. The marital status is obtained from the Statistics Sweden.
Disposable Income	The average individual disposable income (over the years an individual is included in our sample), as defined by Statistics Sweden, that is, the sum of income from labor, business, and investment, plus received transfers, less taxes and alimony payments. Expressed in nominal Swedish Krona (SEK) (unless indicated otherwise). The data are obtained from Statistics Sweden.
Financial Assets	The average end-of-year market value of an individual's financial assets (over the years an individual is included in our sample) as reported by Statistics Sweden, expressed in nominal Swedish Krona (SEK) (unless indicated otherwise). Financial assets include checking, savings, and money market accounts, (direct and indirect) bond holdings, (direct and indirect) equity holdings, investments in options and other financial assets such as rights, convertibles, and warrants.
Total Assets	The average end-of-year market value of an individual's financial and real assets (over the years an individual is included in our sample) as reported by Statistics Sweden, expressed in nominal Swedish Krona (SEK) (unless indicated otherwise).
Net Worth	The average difference between the end-of-year market value of an individual's assets and her liabilities (over the years an individual is included in our sample), as reported by Statistics Sweden. Expressed in nominal Swedish Krona (SEK) (unless indicated otherwise). We form indicator variables that indicate whether an individual's networth is in the first, second, third, or first quartile of the net-worth distribution.
Number of Stocks and Equity Mutual Funds	The average end-of-year number of holdings of distinct individual stocks and equity mutual funds (over the years an individual is included in our sample), as reported by Statistics Sweden.
Value of Stocks and Equity Mutual Funds	The average end-of-year market value of holdings of individual stocks and equity mutual funds (over the years an individual is included in our sample), as reported by Statistics Sweden. Expressed in nominal Swedish Krona (SEK) (unless indicated otherwise).
Number of Stocks	The average end-of-year number of holdings of distinct individual stocks (over the years an individual is included in our sample), as reported by Statistics Sweden.
Value of Stocks	The average end-of-year market value of holdings of individual stocks (over the years an individual is included in our sample), as reported by Statistics Sweden. Expressed in nominal Swedish Krona (SEK) (unless indicated otherwise).
Number of Equity Mutual Funds	The average end-of-year number of holdings of distinct equity mutual funds (over the years an individual is included in our sample), as reported by Statistics Sweden.
Value of Equity Mutual Funds	The average end-of-year market value of holdings of equity mutual funds (over the years an individual is included in our sample), as reported by Statistics Sweden. Expressed in nominal Swedish Krona (SEK) (unless indicated otherwise).
Contact Intensity	The number of contacts per year between twins. The number is calculated as the average of the numbers reported by both twins. If only one twin provides a number, this number is used. The data are obtained from the Swedish Twin Registry.
Distance to Birthplace	The driving distance in kilometers to the state of birth. We define this distance to be the average distance to the center of all municipalities within the state of birth weighted by their population. The distance is obtained from Google Maps. The population numbers are obtained from Statistics Sweden.
Spouse from Home Region	An indicator variable available for married individuals that takes on the value of one if the spouse was born in the same state as the individual and zero otherwise.

Appendix Table A2
Education as a Moderator

	Years of Education		Bias Index
Moderator		**Investment Bias Index**	
a_m	0.2300	*a_c*	0.0010
	0.010		0.129
c_m	-0.1300	*alpha_c*	-0.0209
	0.010		0.112
e_m	0.1100	*a_u*	0.3940
	0.000		0.121
		alpha_u	0.3483
			0.109
		c_c	-0.0950
			0.168
		chi_c	0.2161
			0.152
		c_u	-0.0790
			0.211
		chi_u	0.3082
			0.192
		e_c	0.0290
			0.060
		epsilon_c	-0.0384
			0.108
		e_u	0.9830
			0.060
		epsilon_u	0.0774
			0.049
N		11,800	

Appendix Table A2 reports parameter estimates and standard errors (s.e.) from maximum likelihood estimation of gene-environment interactions models (see Figure 2 for a presentation of the model). The moderator variable is education as measured by years of education (divided by 10 for computational reasons). The Bias Index is based on financial behaviors related to direct stock holdings only. In a first stage (untabulated), we have removed (via linear regression) the effect of control variables listed in Table 4, with the exception of those related to education. *N* provides the number of observations.

Figure 1
Correlations by Genetic Similarity

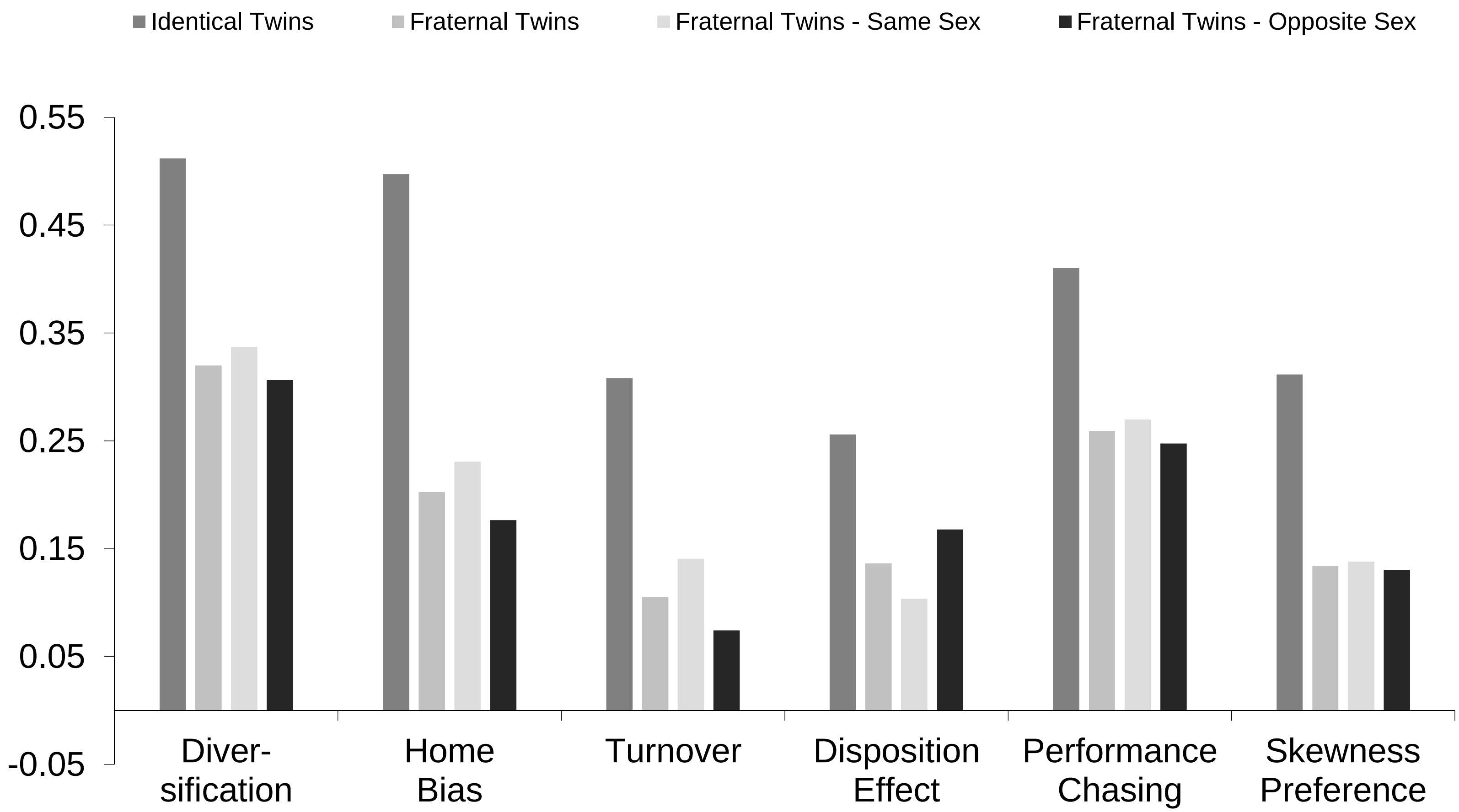

Figure 1 repots Pearson correlation coefficients for *Diversification*, *Home Bias*, *Disposition Effect*, *Performance Chasing,* and *Turnover* between twins for different types of twin pairs. Investment behaviors are calculated using holdings and transactions of direct stock holdings only. All variables are defined in Appendix Table A1.

Figure 2
Gene-Environment Interaction

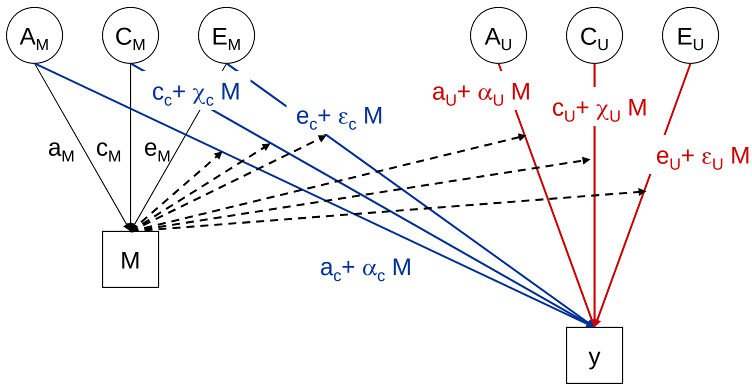

Figure 2 presents a graphical presentation of the gene-interaction model proposed by Purcell (2002). *M* symbolizes the moderator and *y* the Investment Bias Index. *A*, *C*, and *E* correspond to the unobservable genetic and environmental factors. See Purcell (2002) for details.

Figure 3
Education as a Moderator

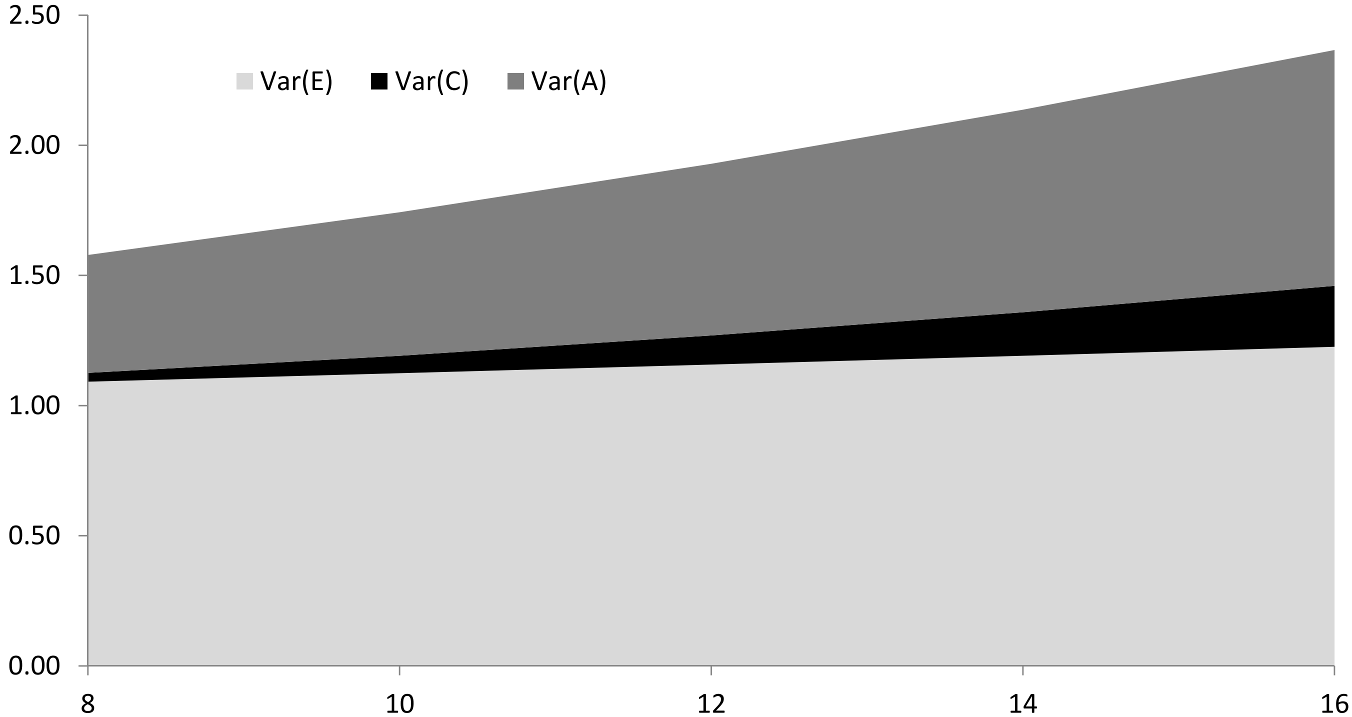

Figure 3 presents results of the gene-interaction model proposed by Purcell (2002). *Years of Education* acts as the environmental moderator. The *x*-axis represents years of education, while the *y*-axis represents the residual variance of the Investment Bias Index, due to genetic effects (A – blue), the common environment (C – red) and the individual-specific environment (E – green). See Appendix Table A2 for detailed estimation results.