Why Do Individuals Exhibit Investment Biases?*

Henrik Cronqvist and Stephan Siegel†

First draft: September 19, 2011
This draft: February 19, 2012

Abstract

We find that a long list of investment biases, e.g., the reluctance to realize losses, performance chasing, and the home bias, are "human," in the sense that we are born with them. Genetic factors explain up to 50% of the variation in these biases across individuals. We find no evidence that education is a significant moderator of genetic investment behavior. Genetic effects on investment behavior are correlated with genetic effects on behaviors in other domains (e.g., those with a genetic preference for familiar stocks also exhibit a preference for familiarity in other domains), suggesting that investment biases is only one facet of much broader genetic behaviors. Our evidence provides a biological basis for non-standard preferences that have been used in asset pricing models, and has implications for the design of public policy in the domain of investments.

*We are thankful for comments from seminar participants at Caltech, Copenhagen Business School, Erasmus University, Institute for Financial Research (SIFR), Maastricht University, Tilburg University, and valuable discussions with Peter Bossaerts, Colin Camerer, Peter Cziraki, David Hirshleifer, Arvid Hoffmann, Søren Hvidkjær, Manjari Quintanar-Solares, Lasse Pedersen, Thomas Post, Paolo Sodini, Elvira Sojli, Oliver Spalt, Per Strömberg, Frank Yu, and Paul Zak. We acknowledge generous research funding from the 2011-12 Faculty Research Award of the Betty F. Elliott Initiative for Academic Excellence, College of Business, The University of Michigan - Dearborn. We thank Florian Münkel, Lucas Perin, and Lew Thorson for excellent research assistance, and Jack Goldberg (Twin Registry at University of Washington) and Nancy Segal (Twin Studies Center at California State University, Fullerton) for advice related to twins studies. This project was pursued in part when Cronqvist was Olof Stenhammar Visiting Professor at SIFR, which he thanks for its support. Statistics Sweden and the Swedish Twin Registry (STR) provided the data for this study. STR is supported by grants from the Swedish Research Council, the Ministry of Higher Education, AstraZeneca, and the National Institute of Health (grants AG08724, DK066134, and CA085739). Any errors or omissions are our own.

†Cronqvist: McMahon Family Chair in Corporate Finance, George R. Roberts Fellow, and Associate Professor of Financial Economics, Claremont McKenna College, Robert Day School of Economics and Finance (hcronqvist@cmc.edu); Siegel: Visiting Assistant Professor of Finance, W. P. Carey School of Business, Arizona State University; Assistant Professor of Finance and Business Economics, Michael G. Foster School of Business; University of Washington (ss1110@uw.edu).

I Introduction

The list of investment biases that individuals exhibit is long. Individuals are, for example, reluctant to realize losses (Odean (1998)), trade too much (Odean (1999)), extrapolate recent superior performance (Patel, Zeckhauser, and Hendricks (1991) and Benartzi (2001)), are insufficiently diversified (French and Poterba (1991)), and have a preference for skewness and lottery-type stocks (Kumar (2009)). These biases have been attributed to psychological mechanisms: Mental accounting combined with prospect theory for the reluctance to realize losses (Thaler (1985) and Kahneman and Tversky (1979)), overconfidence for excessive trading (Fischhoff, Slovic, and Lichtenstein (1977) and Griffin and Tversky (1992)), representativeness and the hot hands fallacy for excessive extrapolation of past performance (Tversky and Kahneman (1974) and Griffin and Tversky (1992)), ambiguity aversion and familiarity for lack of diversification (Ellsberg (1961) and Heath and Tversky (1991)), and cumulative prospect theory for skewness preferences (Tversky and Kahneman (1992)).

Despite this long list of investment biases, little research has been devoted to understanding *why* individuals exhibit these behaviors.[1] Are we born with these investment biases, i.e., are they innate so that we are genetically endowed with them? Or do we exhibit them as a result of our upbringing, learning, or specific environmental experiences? The origins of investment biases have implications for models of investor behavior and asset prices, the extent to which market incentives may be expected to reduce investment biases, and the design of public policy. In this study, we therefore take a first step towards uncovering the origins of investment biases.

Empirically separating the explanation that we are born with investment biases from the alternative that they are learned is very challenging. We therefore use empirical methodology previously used extensively in quantitative behavioral genetics (see, e.g., Neale and Maes (2004) for a review), and more recently in finance and economics research (e.g., Barnea, Cronqvist, and Siegel (2010) and Cesarini et al. (2010)).[2] Our method involves examining data on the investment behaviors of identical and fraternal 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.

[2] An incomplete list of studies in economics which use data on twins include Taubman (1976), Behrman and Taubman (1989), and Ashenfelter and Krueger (1994).

Our data set from the world's largest twin registry, the Sweden Twin Registry, matched with very 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 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, a long list of investment biases are "human" in the sense that we are born with them. We base this conclusion on empirical evidence that genetic factors explain up to 50% of the variation in these biases across individuals. Second, we find no evidence that education is a significant moderator of genetic investment behavior, i.e., genetic predispositions to investment biases can not be easily educated away. Finally, genetic effects on investment behavior are correlated with genetic effects on behaviors in other domains (e.g., those with a genetic preference for familiar stocks also exhibit a preference for familiarity in other domains), suggesting that genetic investment biases is only one facet of much broader individual behavior.

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 reports our results and robustness checks. Section V reports evidence on extensions, e.g., gene-environment interactions effects. Section VI concludes.

II The Origins of Investment Biases

A The Evolution of Non-Standard Preferences and Beliefs

If investment behaviors are genetic, then they propagate from generation to generation. This raises the question of why biases would survive natural selection and not "die out." Some economists' answer is that the the psychological mechanisms behind these behaviors are *fitness* maximizing, i.e., they maximize the likelihood of human survival and reproduction. More specifically, several recent models show that behaviors such as loss aversion and overconfidence are fitness maximizing (e.g., Rayo and Becker (2007), McDermott, Fowler, and Smirnov (2008), Brennan and Lo (2009), and Johnson and Fowler (2011)).[3] That is, the approach of these models is to characterize the end point of a natural selection process in which the fitness-maximizing utility function has come to dominate all other utility functions.

It should be emphasized that the evolution of human preferences started, not in a modern environment, but in a hunter-gatherer society hundreds of thousands of years ago. Some economists have therefore argued that preferences that were fitness-maximizing in such an environment may not be optimal in today's modern environment, potentially explaining why individuals exhibit investment (and other) biases. As Rayo and Becker (2007) conclude (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."

B Born with Biases

Some evidence suggests that the psychological mechanisms behind investment biases are partly genetic. First, the same biases found in humans are also found in genetically close animals. For example, Chen, Lakshminarayanan, and Santos (2006) show that capuchin monkeys exhibit loss aversion, and Lakshminarayanan et al. (2011) find that capuchins have a preference for gambles in which good outcomes are framed as gains rather than payoff-identical gambles in which poor outcomes are framed as losses. As capuchins lack experience with markets and money, Chen et al. (2006) and Santos (2008) conclude that the biases are more likely to be genetic rather than learned: "[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).

[3] Other models of the natural selection of certain preferences and human behaviors include Rogers (1994), Waldman (1994), Robson (1996a,b, 2001a,b), and Netzer (2009). Some of these papers explain why humans have utility functions and time and risk preferences, while others explain why biases may have evolved and survived natural selection (e.g., Waldman (1994)). Some evolutionary models have also appeared in financial economics (e.g., Luo (1998) and Hirshleifer and Luo (2001)). For example, Hirshleifer and Luo (2001) model the effect of natural selection and the long-term survival of overconfident investors in a competitive securities market.

Second, some biases are also found in children at a very early age. For example, 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.

C The Biological Basis for Investment Biases

In this subsection, we review recent empirical evidence regarding the genetic and neuroscientific basis for well-recognized investment biases.[4] Table 1 summarizes our review.

C.1 Insufficient Diversification

A lot of existing evidence shows that individual investors diversify their portfolios much less than is recommended by standard models in financial economics. For example, they overweight stocks from the home market (e.g., French and Poterba (1991)). Such a home bias has not been easy to explain based on standard models (e.g., Lewis (1999)).[5]

Ambiguity aversion and familiarity (e.g., Ellsberg (1961), Heath and Tversky (1991), and Fox and Tversky (1995)) is an alternative approach to explain lack of diversification. Individual investors may find their own home stock market to be much more familiar – and less ambiguous – than international stock markets. Investors overweight familiar securities, and invest little to nothing in ambiguous securities. As a result, their portfolios seem insufficiently diversified compared to predictions of standard models.

Based on recent research in the intersection of economics and neuroscience, we predict that ambiguity aversion and familiarity bias are partly genetic. A gene association study by Chew

[4]For extensive reviews of research at the intersection of neuroscience, genetics, and economics, we refer to Camerer, Loewenstein, and Prelec (2005) and Benjamin et al. (2008).

[5]Home bias is not the only example of insifficient diversification. Huberman (2001) finds that investors are much more likely to hold shares in their local U.S. Regional Bell Operating Companies (RBOCs) than in out-of-state RBOCs. Grinblatt and Keloharju (2001a) find that investors are more likely to hold and trade stocks of firms which are located close to them geographically, which use their native language for company reporting, and whose CEO has their own cultural background. Studies of voluntary contributions by employees in 401(k) plans find a strong bias towards holding own company stock (e.g., Benartzi (2001)). There is no clear information explanation for the results in French and Poterba (1991), Huberman (2001), and Benartzi (2001), and Grinblatt and Keloharju (2001a) argue against such an explanation.

et al. (2011) identifies the genes that affect ambiguity aversion and familiarity. In addition, the neuroimaging study by Hsu et al. (2005) shows that certain parts of the brain were predictably more active under the condition of familiarity than under the condition of ambiguity.

C.2 Excessive Trading

One of the most important stylized facts about individual investors is that some of them trade too much (e.g., Odean (1999)), i.e., they trade much more than may be justified on rational grounds, and such excessive trading may result in losses for the investor (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)). Table 1 reports references to research that finds a relation between genes, overconfidence, and sensation seeking.

C.3 Disposition Effect

Prior research has shown that individual investors exhibit a "disposition effect," i.e., they are reluctant to realize losses on their investments (e.g., Odean (1998), Grinblatt and Keloharju (2001b), Barber et al. (2007), and Dhar and Zhu (2006)).[6] 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 stock investments with a gain than those with a loss.

There are several reasons based on existing research to expect that we are born to exhibit a disposition effect. First, a 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. Second, neuroimaging studies report evidence on the neural basis of loss aversion and the disposition effect (Tom et al. (2007) and Frydman, Barberis, Camerer, Bossaerts, and Rangel (2011)). Finally, the evidence, discussed above, of significant loss aversion and framing effects in animals that are genetically close to humans also suggests that we are born with the disposition

[6] Even professional traders at the Chicago Board of Trade and the Chicago Mercantile Exchange have been found to exhibit the disposition effect (Coval and Shumway (2005) and Locke and Mann (2005)).

effect (e.g., Chen, Lakshminarayanan, and Santos (2006) and Lakshminarayanan et al. (2011)).

C.4 Performance Chasing

Pre-existing research has shown that 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), Benartzi (2001), and Cronqvist and Thaler (2004)). 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 research in neuroeconomics that directly links excessive extrapolation to genes.[7] As a result, our work is one of the first attempts to analyze the extent to which we are hard-wired to exhibit excessive extrapolation in the context on investments.

C.5 Skewness Preference

Several existing studies show that individual investors exhibit a strong preference for stocks with positive skewness, i.e., they like lottery-type stocks (e.g., Kumar (2009)).[8] Such behavior is expected if investors make decisions based on cumulative prospect theory (Tversky and Kahneman (1992) and Barberis and Huang (2008)). Under cumulative prospect theory, investors evaluate risk using a value function that is concave over gains and convex over losses, using probabilities that are transformed from objective probabilities by applying a weighting function which overweights the tails of the distribution it applies it to.

There are several reasons based on existing research to expect that we are born with a preference for skewness. First, studies have found that the preference to gamble has a significant genetic

[7] Two contemporaneous twin studies use a questionnaire and the "Linda question" (Tversky and Kahneman, 1983) to study the genetics of representativeness, but their respective conclusions are very different: Cesarini et al. (2011) report a correlation among identical twins' responses of 0.252 (p-value < 0.01), compared to -0.082 in Simonson and Sela (2011). For fraternal twins, Cesarini et al. (2011) report a correlation of 0.048, compared to 0.451 (p-value < 0.05) in Simonson and Sela (2011). These differences raise concerns about inferences based on questionnaires

[8] For an example of skewness preferences from another domain than investments, see Golec and Tamarkin (1998).

component (e.g., Slutske et al. (2000) and Ibáñez et al. (2003)). Second, a 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. Again, we refer to Table 1 for details.

D Learning to be Biased

The investment behaviors discussed above may alternatively originate from our upbringing and social learning, as opposed to genes. In models of "direct vertical socialization" children are born without defined preferences, and they are first exposed to their parents' socialization (e.g., Bisin and Verdier (2001)). 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 and labor supply preferences (e.g., Bisin and Verdier (2000) and Fernandez, Fogli, and Olivetti (2004)), but they may extend to investment behavior. That is, children may learn certain investment behaviors from their parents.

The environment may influence investment biases in other ways than through upbringing and social learning. 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. That is, there is evidence to expect that individual-specific experiences also affect investment behavior.

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.[9] Importantly, STR's data enables us to determine the zygosity of

[9]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).

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.[10]

Until 2007, taxpayers in Sweden were subject to a wealth tax on assets other than businesses. 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, 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.[11] 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., equity and mixed mutual funds and individual stocks. We 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 holdings data. Panel A of Table 2 reports summary statistics for our data set, which by construction corresponds to 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)), and we have also checked that

[10] 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? The 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.

[11] 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.

the twins are not significantly different from non-twins in terms of socioeconomic characteristics or investment behavior (not tabulated).

Panel B reports summary statistics separately for identical and fraternal twins. All variables are defined in Appendix Table A1. Socioeconomic characteristics are averaged over those years an investor is in our data set.[12] 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) equity securities with a combined value of about $20,000 ($4,000) in the portfolio.[13] About 80% hold at least one equity mutual fund, and about 40% hold at least one stock.

C Measures of Investment Biases

C.1 Insufficient Diversification

We measure *Diversification* by the proportion invested in mutual funds, but not invested in individual stocks. We measure an individual's *Home Bias* by the proportion Swedish securities in the equity portfolio. For each investor and year, we add the market value of Swedish stocks and the Swedish equity allocation of mutual funds, and divide by the total market value of equity holdings. We classify stocks as Swedish or foreign based on the country in which the stock is registered, as reflected by the ISIN. For mutual funds, we collect annual fund-specific data from Morningstar. For funds not covered by Morningstar we infer the fund's investment focus from the fund's name. Finally, to reduce measurement error, we calculate the equally weighted average *Diversification* and *Home Bias* across all years the individual is in the data set. In Table 3, we report summary statistics for both measures, showing that on average investors hold about 70% of their equity portfolio in mutual funds and about 50% in Swedish assets. Focusing on direct stock holdings, the home bias increases to about 94%.

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

[13] 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 IV, 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

We note that the home bias may be explained by transactions costs, some of which may have a genetic component. For example, high transactions costs for investors with insufficient wealth may effectively constrain them from investing in certain international stock markets. A genetic component of home bias may thus simply reflect that wealth has a genetic component. When we estimate our models in Section IV we therefore control for measures of the cross-sectional variation in transactions costs, e.g., wealth. In addition, while investors may overweight the home market because of information they have, we do not consider this to be very likely. First, during our sample period Sweden represents about 1% of the world equity market, while the home bias, on average, is 75 times larger; this discrepancy can not be easily attributable to an information explanation. Second, there is little evidence that individual investors outperform in their local stock investments (e.g., Seasholes and Zhu (2010)). If individual investors do not outperform even in their local stock investments, it seems unlikely that the home bias represents information about Sweden versus other markets.

C.2 Excessive Trading

One of the most important stylized facts about individual investors is that some of them trade too much (e.g., Odean (1999)). A question in this context is then what "too much" trading is. Individuals may trade for different reasons, most importantly portfolio rebalancing due to liquidity demands, which may partly be related to factors that are genetic. For example, deteriorating health, which is partly genetic, may result in more trading to liquidate a portfolio. As a result, a genetic component of trading may thus simply reflect that liquidity demand has a genetic component. When we estimate our models in Section IV we therefore control for an extensive set of socioeconomic characteristics which may correlate with liquidity demands and thus trading. As a result, the measure of trading we decompose may be considered an "excessive trading" measure.[14]

We measure *Turnover*, i.e., an individual's propensity to trade and turnover her investment portfolio in the spirit of 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

[14]Grinblatt and Keloharju (2009) use a similar approach of controlling for socioeconomic characteristics in their analysis of the effect of sensation seeking, measured by the number of speeding tickets, on trading.

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.[15]

Table 3 reports summary statistics, and we find that the turnover for stocks in our data is similar to that reported by Grinblatt and Keloharju (2009) for a large sample of individual investors in Finland, and Agnew, Balduzzi, and Sundén (2003) for a large set of retirement savings accounts in the U.S. Not surprisingly, the average turnover is significantly lower in our data set than the turnover Barber and Odean (2001) report for investors based on data from a large U.S. discount brokerage firm.

C.3 Disposition Effect

We measure the *Disposition Effect* in the spirit of Odean (1998) and Calvet et al. (2009a,b). Specifically, at the end of each year during which we observe at least on sales transaction, we classify all securities in an investor's portfolio as winners or losers based on the security's raw return during the year.[16] Finally, following Odean (1998), we calculate the difference between the proportion of gains realized to the total number of realized and unrealized gains (PGR) and the proportion of losses realized to total losses (PLR). The larger the difference between PGR and PLR, the more reluctant is the investor to realize losses.

In Table 3, we report summary statistics. We calculate our measure of the disposition effect separately for stocks only as well as for stocks and equity mutual funds. We find that the average and median investor in individual stocks exhibits a disposition effect between 3 and 7%. When considering holdings of stocks and equity mutual funds the average disposition effect is close to zero. Most importantly, given that the PGR – PLR difference is bounded by -1 and $+1$, the standard

[15] It is well-recognized that the distribution of turnover may be skewed. To avoid that our analysis may be influenced by a few outliers, we exclude observations for which turnover is higher than the top 1% of the distribution of individual investor turnover.

[16] We use returns to identify winners and losers as we do not observe purchase prices. Odean (1998) points out there are several possible choices of a reference point (e.g., average, first, highest, or most recent), but finds that the results are similar for each choice.

deviation of about 0.40 for both identical and fraternal twins shows that there is significant variation across individuals with respect to the reluctance to realize losses.

C.4 Performance Chasing

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 raw returns during the year. For each investor that has purchases securities during our sample periods, we calculate performance chasing as 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.[17] In Table 3, we report summary statistics, and find consistent with other research that a significant portion of investors seems to chase past performance.

C.5 Skewness Preference

We measure an individual's *Skewness Preference* in the spirit of Kumar (2009). Specifically, 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.[18] *Skewness Preference* is then the fraction of lottery securities averaged over all years with portfolio data. Summary statistics in Table 3 suggest that on average about 5% of an investor's portfolio is held in lottery securities. Importantly, there is substantial variation across investors.

[17] All investors may not be performance chasers. Barber and Odean (2008) find that individuals invest disproportionately in stocks that have caught their attention, e.g., stocks with very high or very low recent returns.

[18] 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.

IV Results

A Evidence from Correlations

Using investment behaviors constructed for the direct equity holdings, Figure 1 reports the correlation for each measure between twins. We draw several conclusions from the evidence. First, for each measure, we find that the correlation is significantly greater between identical than fraternal twins. This difference indicates that investment biases are explained, in part, by a significant genetic component, but genes do not completely explain these behaviors because the correlation for identical twins is significantly different from one. On average, the difference in correlations is 0.2. Second, the correlations for same-sex fraternal twins are greater than those for opposite-sex twins.[19] Finally, the correlation between twins and random age- and gender-matched non-twins is close to zero (on average, 0.004). This is to be expected if either genes or the common parental environment affects investment biases.

B 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 possibly nonlinear 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 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.

Identifying variation due to a_{ij}, c_i, and e_{ij} separately is possible due to constraints on the covariances from genetic theory. Consider two twin pairs $i = 1, 2$ with twins $j = 1, 2$ in each pair,

[19] We examine difference between same-sex and opposite-sex twins in the robustness section

where the first is a pair of identical twins and the second is a pair of fraternal twins. The genetic effects are: $a = (a_{11}, a_{21}, a_{12}, a_{22})'$. Analogously, the common and individual-specific environmental effects are: $c = (c_{11}, c_{21}, c_{12}, c_{22})'$ and $e = (e_{11}, e_{21}, e_{12}, e_{22})'$. Identical and fraternal twin pairs differ in their genetic similarity. Identical twins are genetically identical, and the correlation between a_{11} and a_{21} 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, a 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.

C 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. We follow pre-existing research and control for several standard observable socioeconomic characteristics (e.g., Agnew (2006) and Calvet, Campbell, and Sodini (2009b)). Some of these characteristics, for example wealth, have been found to have a genetic component. By controlling for these characteristics, we attempt to capture variation across individuals that is attributable to differences in *preferences*, as opposed to differences in individual observable characteristics that are genetic.

Table 4 reports the estimated coefficients on the included control variables, and most importantly, the variance components A, C, and E for each of the investment behaviors. We draw several conclusions from the evidence in the table. First, 26-45%, depending on investment behavior, of the variation in investment biases across individual investors is attributable to our genes, as opposed to the environment. That is, we are to a significant extent born with the investment bias we examine in this paper. Second, as the C component is very close to zero for each bias, we find very little evidence that upbringing (or other aspects of the common environment) affects investment biases. That is, the notion that children learn investment biases from their parents is inconsistent with the data.[20] Finally, we find that over 50% of the variation across individuals is attributable to individual-specific experiences.

We find that modeling a genetic component, a_{ij} in equation (2), improves the fit of a model that explains the cross-sectional variation in investment biases. Specifically, while we only report results for "ACE models" in the table, we have also estimated a "CE model," in which A is set to zero and an "E model," in which both A and C are both set to zero. To compare the fit of these models, we compute the Satorra-Bentler scaled χ^2 and test for the difference in χ^2 for an ACE versus CE model and a CE versus E model. We conclude that modeling an unobservable genetic factor significantly improves the fit of a model that attempts to explain the variation in investment biases across individual investors.

[20]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)).

D Size of Portfolio

Some of the portfolios we have analyzed so far are small relative to the individual's total assets. In Table 5, we therefore exclude all individuals for whom the equity portfolio does not constitute at least 20% of their total assets. This reduces the sample size significantly, but it enables us to exclude those for whom the equity portfolio is insignificant and who may therefore not have strong incentives to carefully consider their investment behaviors. We include the same individual socioeconomic characteristics as previously, but we only report the variance components A, C, and E. Overall, we find that the A components of the investment biases increases. They are 30-53%, depending on investment behavior. That is, we find a significant genetic effect on investment behavior also among those for whom the equity portfolio is significant and who may have the strongest incentives to carefully consider their investment behaviors.

E Impact of Delegated Portfolio Management

Does delegated portfolio management reduce the effect of genes on investment biases? On the one hand, individual investor may attribute mutual fund losses, not to oneself, but to the managers of the funds, and as a result any genetic predisposition to, e.g., loss aversion may not be as strong for mutual funds as for individual stock investments. On the other hand, portfolio management comes with its own agency problems (e.g., Bergstresser, Chalmers, and Tufano (2009)).

Our analysis so far has involved only individual stocks, but in Table 6 we also include mutual fund investments. We first report in the table that the extent to which individuals diversity their portfolios is genetic (A = 39%). We then re-estimate the models previously reported for stock investments only, but find that the A components of the investment biases do not change very much. We conclude that delegated portfolio management does not seem to be a way for individual investors to significantly "debias" themselves from investment biases they may be born with.[21]

[21]For evidence on behavioral biases of mutual funds investors, see, e.g., Bailey et al. (2010).

F Robustness Checks

F.1 Opposite-Sex Twins

We noted when discussing Figure 1 above that the correlations for same-sex fraternal twins are greater than those for opposite-sex twins. A concern is that opposite-sex twins make fraternal twins more different compared to identical twins, which may result in an upward bias of A. We included gender as a control in all of the previously estimated models, but as a robustness check, we also exclude opposite-sex fraternal twins from our sample, and re-estimate the models. Panel A of Table 7 shows that our results do not change much compared to the estimates previously reported in Table 4.

F.2 Model Misspecification

One concern with some of the reported C components in Table 4 is that they are exactly zero. This is because we constrain the variances to be non-negative, but suggests that the models may be misspecified. As a robustness check, we therefore re-estimate the model in equation (2), but without the non-negativity constraints on the variances. Panel B shows that the the C components are very small (-3.9% to -7.6%) and not 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), but we have checked and found that a Tobit model specification results in unchanged, or sometimes stronger, A components (not tabulated).

F.3 Model Assumptions

One concern is the model assumption that the common environment is not more important for identical twins than for fraternal twins.[22]

Parenting. If the parents of identical twins treat their twins more similarly than the parents of fraternal twins treat their twins, then A may be upward biased. Researchers have used twins

[22] See, e.g., Goldberger (1979), Taubman (1981), and Bouchard and McGue (2003) for a further discussion of model assumptions and some of the common concerns with respect to analysis of data on twins.

reared apart, i.e., twins separated at birth or early in life, for which there is no common parental environment, to address this problem. While we do not have sufficiently many reared apart twin pairs in our sample to perform any statistical analysis, we note that other researchers report that an analysis of reared apart twins does not change the conclusions (e.g., Bouchard et al. (1990)).

Social Interaction. If identical twins interact more 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 be upward biased. We address this concern using two robustness checks. First, we exclude twin pairs with significant, i.e., more than 50%, portfolios similarity. Panel C reveals that our results are generally robust to excluding twins with similar portfolios. Second, we sort twin pairs into deciles based on social interaction, in particular the communication frequency between twins, and randomly exclude twins until we have equally many identical or fraternal in each decile. Panel D of Table 7 reports that the A components are generally still large and statistically significantly. Only for *Performance Chasing*, we no longer find a significant genetic effect once we control for social interaction. As Hirshleifer (2010) points out, investors are more likely to exchange information about securities that have done particularly well, suggesting that more communication between identical twins might indeed lead to more similar behavior with respect to *Performance Chasing*. To see whether or not this finding obtains in the overall portfolio, we repeat the analysis using stocks and mutual funds. For the combined portfolio, we find that controlling for social interaction between twins still leads to a substantial and significant A component and a small and insignificant C component.[23] Hence, it is also possible that our finding for *Performance Chasing* with respect to directly held stocks is an outcome of the specific, relatively small sample used in the analysis in Panel D.

Another model assumption is random mating. While economists have examined non-random mating based on, e.g., education, we are not aware of any studies of mating based on investment behavior. Positive assortative mating between the twins' parents make fraternal twins more similar relative to identical twins and would bias A downwards.

[23]Specifically, using 12,736 observations, we estimate A to be 0.247 ($s.e. = 0.055$), while C is estimated to be 0.022 ($s.e. = 0.041$).

F.4 Measurement Error

Measurement error in y_{ij} is captured by e_{ij} in the model in equation (2). As a result, the A component may be downward biased if there is significant measurement error in data. Because our data set comes from the Swedish Tax Agency, which in turn obtain their data directly from financial institutions, we consider measurement error to be rare in our data. In addition, we have attempted to reduce measurement error by averaging all measures of investment biases across all years with available data for an individual.

F.5 Amount of Environmental Variation

A remaining concern is that an estimated genetic component is not a universal constant, but an estimate relative to the amount of genetic and environmental variation in the sample. The variance decomposition we perform and therefore our estimates of the relative importance of genetic variation are from a specific country, i.e., Sweden, during a specific time period, i.e., 1999–2007. It is possible that the relative contribution of genetic and environmental variation differs between different countries. We are not able to address this concern explicitly as we have data from only one country, but we note that there is indeed a significant amount of variation is both the investment behaviors and various individual socioeconomic characteristics in our data.

V Extensions

We have reported evidence that genetic effects explain each of the investment biases we examine. In this section, we report two extensions. First, we examine whether some factors moderate the genetic effect on investment behaviors ("gene-environment interactions").[24] Second, we examine whether genetic effects on investment behavior are correlated with genetic effects on non-financial behaviors ("genetic correlations").

[24] For an extensive review of research on gene-environment interactions, we refer to Rutter (2006).

A Gene-Environment Interactions

Education is a potentially significant moderator for genetic effects. For example, Johnson et al. (2010) show, in another context than ours, that education reduces expressions of genetic predispositions to poor health. That is, individuals may be born with a propensity to poor health, but education reduces such propensities. In this paper, it is natural to examine the extent to which education moderates genetic effects on investment behavior.

We use 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) interacts with the unobservable genetic and environmental factors of the investment behavior (y). The model allows for the moderator and the investment behavior to be correlated via exposure of the investment behavior to the unobservable genetic and environmental factors of the moderator. In a first stage (not tabulated), we use regressions to remove the effect of the socioeconomic characteristics used as control variables in Table 4, with the exception of the moderators.

Figure 3 reports results with education (measured as number of years of education) as the moderator. We do not find that education is a significant moderator of genetic investment biases. The coefficient $alpha_u$ in Table 8 is not statistically significant. This evidence is important in that it suggests that genetic predispositions to investment biases is not altered by general education.

Our education result raises the question of whether experience, specifically with respect to finance, reduces genetic investment biases. We estimate separate models for individuals with financial experience. Specifically, we use data on individuals' 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. For those twins with finance experience, we find in Table 9 a smaller genetic effects on *Diversification*, *Home Bias*, *Trading*, and *Performance Chasing* measured on all holdings of stock and equity mutual funds.[25] We note that the similar occupational environment experienced by this subset of twins appears to generate commonality in their behavior. Our conclusion is that finance experience seems to reduces genetic effects on investment biases.

[25] We still have too few twin pairs that have finance occupation to estimate a separate model for *Loss Aversion*.

B Genetic Correlations

We also examine whether genetic effects on investment behavior are correlated with genetic effects on behaviors in domains other than investments. A specific example is the preference for familiarity. Individuals may exhibit a preference for the familiar in many different domains, including investments, choice of home location and culture. We 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 the correlation is genetic.

In Table 10, we report results from bivariate models that allow us to jointly decompose the variation in home bias and in another behavior and to analyze whether both behaviors are correlated through the same genetic predisposition. We consider two measures of familiarity preferences in domains other than investments: Home location distance to the birth place and an indicator for whether the individual's spouse is born in the same state an the individual himself or herself. Note that the model controls for individual socioeconomic characteristics that may determine both investment behavior and the other outcomes, e.g., income and wealth.

We report several results from this exercise. First, familiarity in some other, non-investment, domains also has a significant genetic component: 40% for home location choice and 15% for spouse choice. Second, the measures of investment and non-investment domain familiarity are correlated. Those with more home bias in their investment portfolios have a stronger preference for a home location close to their birth place and a spouse who is from that region. Finally, we find that this correlation has a large genetic components, and the genetic correlation with distance to birth location is statistically significant at the 5%-level.

This evidence is important because it suggests that investment biases are facets of much broader individual behavior. For example, we are born with more or less of a preference for the familiar, which affects behavior across both the investment and other domains.

VI Conclusion

We find that a long list of investment biases, e.g., the reluctance to realize losses, performance chasing, and the home bias, are "human," in the sense that we are born with them. We base this conclusion on empirical evidence that genetic factors explain up to 50% of the variation in these biases across individuals. The psychological mechanisms behind the investment biases have apparently survived natural selection over hundreds of thousands of years, presumably because they maximize (or in a hunter-gatherer society used to maximize) the likelihood of human survival and reproduction (e.g., Rayo and Becker (2007) and Brennan and Lo (2009)). But in our current society, and when applied in the domain of investments, they may not always be appropriate.

One implication of our evidence is that it provides a biological basis for modeling investors with non-standard preferences. In a series of papers, Barberis, Huang, and Santos (2001), Barberis and Huang (2008), and Barberis and Xiong (2009)) develop models of the asset pricing implications of investors exhibiting some of the behaviors we analyze. If individuals are genetically endowed with certain non-standard preferences, asset pricing models should reflect such preferences.

Two other result are worth emphasizing. First, we find no evidence that general education is a significant moderator of genetic investment behavior, i.e., the role of genetic predispositions to investment biases does not seem to depend on the level of education. Second, genetic effects on investment behavior are correlated with genetic effects on behaviors in other domains (e.g., those with a genetic preference for familiar stocks also exhibit a preference for familiarity in other domains), suggesting that genetic investment biases is only one facet of much broader individual behavior.

In recent years, significant research and public policy efforts have been devoted to financial literacy (e.g., Thaler and Benartzi (2004), Lusardi and Mitchell (2007), and Campbell et al. (2011)), which raises the question: Does our result that investment biases are partly genetic, and our result that genetic investment biases are not significantly moderated by education, make policy initiatives irrelevant? No, but our evidence has implications for the design of policy initiatives. It suggests that policy should recognize that many individuals indeed exhibit investment biases, and that altering such biases can be difficult.

References

Agnew, J., Balduzzi, P., Sundén, A., 2003. Portfolio choice and trading in a large 401(k) plan. American Economic Review 93 (1), 193–215.

Agnew, J. R., 2006. Do behavioral biases vary across individuals? Evidence from individual level 401(k) data. Journal of Financial and Quantitative Analysis 41 (4), 939.

Ashenfelter, O., Krueger, A. B., 1994. Estimates of the economic returns to schooling from a new sample of twins. American Economic Review 84 (5), 1157–1173.

Bailey, W., Kumar, A., Ng, D., 2010. Behavioral biases of mutual fund investors. Journal of Financial Economics 102, 1–27.

Barber, B., Lee, Y., Liu, Y., Odean, T., 2007. Is the aggregate investor reluctant to realise losses? Evidence from taiwan. European Financial Management 13 (3), 423–447.

Barber, B., Lee, Y., Liu, Y., Odean, T., 2009. Just how much do individual investors lose by trading? Review of Financial Studies 22 (2), 609.

Barber, B., Odean, T., 2008. All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. Review of Financial Studies 21 (2), 785–818.

Barber, B. M., Odean, T., 2000. Trading is hazardous to your wealth: The common stock investment performance of individual investors. Journal of Finance 55 (2), 773–806.

Barber, B. M., Odean, T., 2001. Boys will be boys: Gender, overconfidence, and common stock investment. Quarterly Journal of Economics 116 (1), 261–292.

Barberis, N., Huang, M., 2008. Stocks as lotteries: The implications of probability weighting for security prices. American Economic Review 98 (5), 2066–2100.

Barberis, N., Huang, M., Santos, T., 2001. Prospect theory and asset prices. Quarterly Journal of Economics 116 (1), 1–53.

Barberis, N., Xiong, W., 2009. What drives the disposition effect? An analysis of a long-standing preference-based explanation. Journal of Finance 64 (2), 751–784.

Barnea, A., Cronqvist, H., Siegel, S., 2010. Nature or nurture: What determines investor behavior? Journal of Financial Economics 98, 583–604.

Behrman, J., Taubman, P., 1989. Is schooling “mostly in the genes”? Nature-nurture decomposition using data on relatives. Journal of Political Economy 97, 1425–1446.

Benartzi, S., 2001. Excessive extrapolation and the allocation of 401 (k) accounts to company stock. Journal of Finance 56 (5), 1747–1764.

Benjamin, D., Chabris, C., Glaeser, E., Gudnason, V., Harris, T., Laibson, D., Launer, L., Purcell, S., 2008. Genoeconomics. The National Academies Press, Ch. 15, pp. 304–335.

Bergstresser, D., Chalmers, J., Tufano, P., 2009. Assessing the costs and benefits of brokers in the mutual fund industry. Review of Financial Studies 22 (10), 4129–4156.

Bikhchandani, S., Hirshleifer, D., Welch, I., 1998. Learning from the behavior of others: Conformity, fads, and informational cascades. Journal of Economic Perspective 12 (3), 151–170.

Bisin, A., Verdier, T., 2000. Beyond the melting pot: Cultural transmission, marriage, and the evolution of ethnic and religious traits. Quarterly Journal of Economics 115 (3), 955–988.

Bisin, A., Verdier, T., 2001. The economics of cultural transmission and the dynamics of preferences. Journal of Economic Theory 97 (2), 298 – 319.

Bortolus, R., Parazzini, F., Chatenoud, L., Benzi, G., Bianchi, M., Marini, A., 1999. The epidemiology of multiple births. Human Reproduction Update 5 (2), 179.

Bouchard, T., McGue, M., 2003. Genetic and environmental influences on human psychological differences. Journal of Neurobiology 54 (1), 4–45.

Bouchard, T. J., Lykken, D. T., McGue, M., Segal, N. L., Tellegen, A., 1990. Sources of human psychological differences: The Minnesota study of twins reared apart. Science 250, 223–228.

Brennan, T. J., Lo, A. W., 2009. The origin of behavior. Working Paper, MIT Sloan School of Management.

Calvet, L. E., Campbell, J. Y., Sodini, P., 2009a. Fight of flight? Portfolio rebalancing by individual investors. Quarterly Journal of Economics 124, 301–348.

Calvet, L. E., Campbell, J. Y., Sodini, P., 2009b. Measuring the financial sophistication of households. American Economic Review 99, 393–398.

Camerer, C., Loewenstein, G., Prelec, D., 2005. Neouroeconomics: How neuroscience can inform economics. Journal of Economic Literature 43, 9–64.

Campbell, J., Jackson, H., Madrian, B., Tufano, P., 2011. Consumer financial protection. Journal of Economic Perspectives 25 (1), 91–114.

Cesarini, D., Johannesson, M., Lichtenstein, P., Sandewall, O., Wallace, B., 2010. Genetic variation in financial decision making. Journal of Finance 65, 1725–1754.

Cesarini, D., Johannesson, M., Lichtenstein, P., Wallace, B., 2009. Heritability of overconfidence. Journal of the European Economic Association 7 (2-3), 617–627.

Cesarini, D., Johannesson, M., Magnusson, P. K. E., Wallace, B., 2011. The behavioral genetics of behavioral anomalies. Forthcoming Management Science.

Chen, M. K., Lakshminarayanan, V., Santos, L. R., 2006. How basic are behavioral biases? Evidence from Capuchin monkey trading behavior. Journal of Political Economy 114 (3), 517–537.

Chew, S. H., Ebstein, R. P., Zhong, S., 2011. Ambiguity aversion and familiarity bias: Evidence from behavioral and gene association studies. Forthcoming Journal of Risk and Uncertainty.

Coval, J., Shumway, T., 2005. Do behavioral biases affect prices? Journal of Finance 60 (1), 1–34.

Cronqvist, H., Thaler, R. H., 2004. Design choices in privatized social-security systems: Learning from the Swedish experience. American Economic Review 94 (2), 424–28.

DeMartino, B., Kumaran, D., Seymour, B., Dolan, R., 2006. Frames, biases, and rational decision-making in the human brain. Science 313 (5787), 684.

Dhar, R., Zhu, N., 2006. Up close and personal: Investor sophistication and the disposition effect. Management Science 52 (5), 726–740.

Ellsberg, D., 1961. Risk, ambiguity, and the savage axioms. Quarterly Journal of Economics, 643–669.

Fernandez, R., Fogli, A., Olivetti, C., 2004. Mothers and sons: Preference formation and female labor force dynamics. Quarterly Journal of Economics 119 (4), 1249–1299.

Fischhoff, B., Slovic, P., Lichtenstein, S., 1977. Knowing with certainty: The appropriateness of extreme confidence. Journal of Experimental Psychology: Human Perception and Performance 3 (4), 552.

Fox, C. R., Tversky, A., 1995. Ambiguity aversion and comparative ignorance. Quarterly Journal of Economics 110 (3), 585–603, english.

French, K. R., Poterba, J. M., 1991. Investor diversification and international equity markets. American Economic Review 81 (2), 222–226.

Frydman, C., Barberis, N., Camerer, C., Bossaerts, P., Rangel, A., 2011. Testing theories of investor behavior using neural data. Working paper, Caltech.

Fulker, D. W., Eysenck, S. B. G., Zuckerman, M., 1980. A genetic and environmental analysis of sensation seeking. Journal of Research in Personality 14, 261–281.

Gervais, S., Odean, T., 2001. Learning to be overconfident. Review of Financial Studies 14 (1), 1–27.

Goldberger, A., 1979. Heritability. Economica 46 (184), 327–347.

Golec, J., Tamarkin, M., 1998. Bettors love skewness, not risk, at the horse track. Journal of Political Economy 106 (1), 205–225.

Griffin, D., Tversky, A., 1992. The weighting of evidence and the determinants of confidence. Cognitive Psychology 24, 411–435.

Grinblatt, M., Keloharju, M., 2001a. How distance, language, and culture influence stockholdings and trades. Journal of Finance 56 (3), 1053–1073.

Grinblatt, M., Keloharju, M., 2001b. What makes investors trade? Journal of Finance 56, 589–616.

Grinblatt, M., Keloharju, M., 2009. Sensation seeking, overconfidence, and trading activity. Journal of Finance 64, 549–578.

Harbaugh, W., Krause, K., Vesterlund, L., 2001. Are adults better behaved than children? Age, experience, and the endowment effect. Economics Letters 70 (2), 175–181.

Heath, C., Tversky, A., 1991. Preferences and beliefs: Ambiguity and competence in choice under uncertainty. Journal of Risk and Uncertainty 4 (1), 5–28.

Hirshleifer, D., 2010. Self-enhancing transmission bias and active investing, working paper, University of California, Irvine.

Hirshleifer, D., Luo, G., 2001. On the survival of overconfident traders in a competitive securities market. Journal of Financial Markets 4 (1), 73–84.

Hong, H., Kubik, J. D., Stein, J. C., 2004. Social interaction and stock-market participation. Journal of Finance 59 (1), 137–163.

Hsu, M., Bhatt, M., Adolphs, R., Tranel, D., Camerer, C., 2005. Neural systems responding to degrees of uncertainty in human decision-making. Science 310 (5754), 1680.

Huberman, G., 2001. Familiarity breeds investment. Review of Financial Studies 14 (3), 659–680.

Ibáñez, A., Blanco, C., Perez de Castro, I., Fernandez-Piqueras, J., Sáiz-Ruiz, J., 2003. Genetics of pathological gambling. Journal of Gambling Studies 19:1, 11–22.

Johnson, D. D. P., Fowler, J. H., 2011. The evolution of overconfidence. Nature.

Johnson, W., Kyvik, K. O., Mortensen, E. L., Skytthe, A., Batty, G. D., Deary, I. J., 2010. Education reduces the effects of genetic susceptibilities to poor physical health. International Journal of Epidemiology 39 (2), 406–414.

Kahneman, D., Tversky, A., 1979. Prospect theory: An analysis of decision under risk. Econometrica 47 (2), 263–292.

Kumar, A., 2009. Who gambles in the stock market? Journal of Finance 64 (4), 1889–1933.

Lakshminarayanan, V., Chen, M., Santos, L., 2011. The evolution of decision-making under risk: Framing effects in monkey risk preferences. Journal of Experimental Social Psychology 47, 689–693.

Lewis, K., 1999. Trying to explain home bias in equities and consumption. Journal of Economic Literature 37 (2), 571–608.

Lichtenstein, P., Sullivan, P. F., Cnattingius, S., Gatz, M., Johansson, S., Carlström, E., Björk, C., Svartengren, M., Wolk, A., Klareskog, L., de Faire, U., Schalling, M., Palmgren, J., Pedersen, N. L., 2006. The Swedish twin registry in the third millennium: An update. Twin Research and Human Genetics 9, 875–882.

Locke, P., Mann, S., 2005. Professional trader discipline and trade disposition. Journal of Financial Economics 76 (2), 401–444.

Luo, G., 1998. Market efficiency and natural selection in a commodity futures market. Review of Financial Studies 11 (3), 647–674.

Lusardi, A., Mitchell, O. S., 2007. Financial literacy and retirement preparedness: Evidence and implications for financial education. Business Economics 42, 35–44.

McDermott, R., Fowler, J., Smirnov, O., 2008. On the evolutionary origin of prospect theory preferences. Journal of Politics 70 (2), 335–50.

Muthén, L., Muthén, B., 2010. Mplus user's guide (sixth edition).

Neale, M. C., Maes, H. H. M., 2004. Methodology for Genetic Studies of Twins and Families. NATO ASI Series D: Behavioural and Social Science. Kluwer Academic Publishers B.V., Dordrecht, The Netherlands.

Netzer, N., 2009. Evolution of time preferences and attitudes toward risk. American Economic Review 99, 937–955.

Odean, T., 1998. Are investors reluctant to realize their losses? Journal of Finance 53 (5), 1775–1798.

Odean, T., 1999. Do investors trade too much? American Economic Review 89, 1279–1298.

Patel, J., Zeckhauser, R. J., Hendricks, D., 1991. The rationality struggle: Illustrations from financial markets. American Economic Review 81 (2), 232–236.

Purcell, S., 2002. Variance components models for geneenvironment interaction in twin analysis. Twin Research 5, 554–571.

Rayo, L., Becker, G., 2007. Evolutionary efficiency and happiness. Journal of Political Economy 115 (2).

Robson, A. J., 1996a. A biological basis for expected and non-expected utility. Journal of Economic Theory 68 (2), 397–424.

Robson, A. J., 1996b. The evolution of attitudes to risk: Lottery tickets and relative wealth. Games and Economic Behavior 14, 190–207.

Robson, A. J., 2001a. The biological basis of economic behavior. Journal of Economic Literature 29, 11–33.

Robson, A. J., 2001b. Why would nature give individuals utility functions? Journal of Political Economy 109, 900–914.

Rogers, A. R., 1994. Evolution of time preference by natural selection. American Economic Review 84 (3), 460–81.

Rutter, M., 2006. Genes and behavior: Nature/nurture interplay explained. Blackwell Publishers, Oxford, UK.

Santos, L., 2008. The evolution of irrationality: Insights from non-human primates. Oxford Studies in Epistemology 2, 87–107.

Seasholes, M., Zhu, N., 2010. Individual investors and local bias. Journal of Finance 65 (5), 1987–2010.

Shefrin, H., Statman, M., 1985. The disposition to sell winners too early and ride losers too long: Theory and evidence. Journal of Finance, 777–790.

Simonson, I., Sela, A., 2011. On the heritability of consumer decision making: An exploratory approach for studying genetic effects on judgment and choice. Journal of Consumer Research 37 (6), 951–966.

Slutske, W. S., Eisen, S., True, W. R., Lyons, M. J., Goldberg, J., Tsuang, M., 2000. Common genetic vulnerability for pathological gambling and alcohol dependence in men. Archives of General Psychiatry 7, 666–673.

Taubman, P., 1976. The determinants of earnings: Genetics, family, and other environments: A study of white male twins. American Economic Review 66 (5), 858–870.

Taubman, P., 1981. On heritability. Economica 48 (192), 417–420.

Thaler, R. H., 1985. Mental accounting and consumer choice. Marketing Science 4 (3), 199–214.

Thaler, R. H., Benartzi, S., 2004. Save more tomorrow: Using behavioral economics to increase employee savings. Journal of Political Economy 112, 164–187.

Tom, S., Fox, C., Trepel, C., Poldrack, R., 2007. The neural basis of loss aversion in decision-making under risk. Science 315 (5811), 515.

Tversky, A., Kahneman, D., 1974. Judgment under uncertainty: Heuristics and biases. Science 211, 453–458.

Tversky, A., Kahneman, D., 1983. Extensional versus intuitive reasoning: The conjunction fallacy in probability judgment. Psychological Review 90 (4), 293–315.

Tversky, A., Kahneman, D., 1992. Advances in prospect theory: Cumulative representation of uncertainty. Journal of Risk and Uncertainty 5 (4), 297–323.

Waldman, M., 1994. Systematic errors and the theory of natural selection. American Economic Review, 482–497.

Zhong, S., Chark, R., Ebstein, R., Chew, S., 2011. Imaging genomics for utility of risks over gains and losses. Neuroimage.

Zhong, S., Israel, S., Xue, H., Sham, P., Ebstein, R., Chew, S., 2009. A neurochemical approach to valuation sensitivity over gains and losses. Proceedings of the Royal Society B: Biological Sciences 276 (1676), 4181.

Table 1
The Neuroscientific and 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)
			Neural basis for ambiguity aversion (Hsu et al. (2005))
Excessive trading	Overconfidence	NA	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); Zhong et al. (2011)
		10-repeat vs. 12-repeat allele of STin2	Zhong et al. (2009); Zhong et al. (2011)
			Loss aversion in Capuchin monkeys (Chen et al. (2006))
			Neural basis for loss aversion (Tom et al (2007))
			Neural basis for the disposition effect (Frydman et al. (2011))
	Mental accounting / Framing	NA	Narrow framing in Capuchin monkeys (Lakshminarayanan et al. (2011))
			Neural basis for framing (De Martino et al. (2006))
Performance chasing	Excessive extrapolation	NA	
	Hot hands fallacy	NA	
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 neuroscience and behavioral genetics with respect to investment behaviors examined in this study.

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
Years of Education	17,395	11.22	11.00	3.26	11.11	11.00	3.29
Single	30,416	0.40	0.00	0.48	0.29	0.00	0.44
Married	30,416	0.46	0.00	0.50	0.54	1.00	0.50
Divorced	30,416	0.09	0.00	0.28	0.11	0.00	0.30
Widowed	30,416	0.05	0.00	0.21	0.07	0.00	0.24
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
Fraction of Equity Assets included	30,416	0.89	0.99	0.18	0.89	0.99	0.18
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	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
Finance Occupation (Broad)	16,643	0.17	0.00	0.37	0.16	0.00	0.36
Distance to Birthplace (km)	30,122	112.82	0.00	212.65	109.84	0.00	213.93
Spouse from Home Region	11,009	0.57	1.00	0.49	0.60	1.00	0.49

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							
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	2,268	0.05	0.03	0.41	0.07	0.03	0.41
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
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	5,922	0.01	0.00	0.40	0.00	0.00	0.39
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 financial behavior, *Diversification*, *Home Bias*, *Turnover, Loss Aversion*, *Performance Chasing*, and *Skewness Preference*. All variables are defined in detail in Appendix Table A1.

Table 4
Decomposition of Investment Behaviors

	Home Bias	Turnover	Disposition Effect	Performance Chasing	Skewness Preference
Intercept	0.955	0.134	0.132	2.313	0.004
	0.021	0.039	0.168	0.564	0.010
Male	0.004	0.062	-0.007	0.062	0.008
	0.003	0.008	0.002	0.056	0.002
Age	0.004	0.031	0.011	0.092	0.015
	0.007	0.014	0.040	0.111	0.004
Age - squared	0.000	-0.005	0.000	-0.008	-0.002
	0.001	0.001	0.004	0.011	0.000
High School	-0.001	0.000	-0.010	-0.117	0.001
	0.002	0.004	0.012	0.093	0.001
College or More	-0.012	0.022	-0.032	-0.156	0.005
	0.003	0.008	0.026	0.080	0.002
No Education Data Available	-0.026	0.037	-0.025	-0.002	0.010
	0.005	0.010	0.034	0.057	0.003
Married	-0.001	-0.001	-0.054	-0.051	0.002
	0.004	0.009	0.025	0.057	0.003
Second Net Worth Quartile Indicator	-0.001	-0.005	-0.056	0.122	0.003
	0.003	0.007	0.021	0.081	0.002
Third Net Worth Quartile Indicator	0.001	-0.011	-0.006	0.200	-0.002
	0.003	0.008	0.029	0.084	0.002
Highest Net Worth Quartile Indicator	-0.010	-0.025	-0.007	0.294	-0.004
	0.004	0.008	0.026	0.087	0.002
Log of Disposable Income	-0.001	-0.002	-0.004	0.117	0.000
	0.001	0.002	0.013	0.044	0.000
Number of Trades (Sales)			0.003		
			0.014		
Number of Holdings			-0.003		
			0.001		
A Share	0.453	0.257	0.297	0.311	0.281
	0.052	0.029	0.077	0.090	0.051
C Share	0.000	0.000	0.000	0.096	0.000
	0.027	0.008	0.041	0.065	0.028
E Share	0.547	0.743	0.703	0.593	0.719
	0.037	0.027	0.052	0.038	0.034
R^2	0.010	0.014	0.020	0.009	0.000
N	12,378	11,508	2,268	6,672	12,378

Table 3 reports results from maximum likelihood estimation. The different Financial 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 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). Only direct stock holdings are considered in the measurement of the different financial behaviors. All variables are defined in Appendix Table A1. R^2 denotes the coefficient of variation. *N* provides the number of observations used in each estimation.

Table 5
Individuals with at Least 20% of Total Assets Invested in Risky Financial Assets

		Variance Components		
Model	*N*	*A* - Share	*C* - Share	*E* - Share
Home Bias	2,574	0.525	0.116	0.359
		0.168	0.122	0.072
Turnover	2,306	0.447	0.000	0.553
		0.129	0.069	0.084
Disposition Effect	866	0.451	0.000	0.549
		0.095	0.030	0.087
Performance Chasing	1,814	0.296	0.220	0.484
		0.171	0.132	0.069
Skewness Preference	2,574	0.350	0.047	0.603
		0.164	0.128	0.079

Table 5 reports results from maximum likelihood estimation for the subset of investors with at least 20% of total assets invested in risky financial assets. The different Financial Behaviors are modeled as linear functions of observable socioeconomic variables (see Table 4 for a list of the variables included) 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 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). All variables are defined in Appendix Table A1. *N* provides the number of observations used in each estimation.

Table 6
Delegated Portfolio Management

Model	N	Variance Components *A* - Share	*C* - Share	*E* - Share
Diversification	30,416	0.389	0.022	0.589
		0.032	0.021	0.014
Home Bias	30,416	0.361	0.000	0.639
		0.013	0.003	0.012
Turnover	28,108	0.258	0.000	0.742
		0.022	0.009	0.018
Disposition Effect	5,922	0.198	0.000	0.802
		0.039	0.015	0.032
Performance Chasing	25,530	0.272	0.000	0.728
		0.019	0.002	0.019
Skewness Preference	30,416	0.273	0.000	0.727
		0.036	0.018	0.024

Table 6 reports results from maximum likelihood estimation. The different Financial 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 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).Financial behaviors are derived from all holdings of stocks and equity mutual funds. All variables are defined in Appendix Table A1. R^2 denotes the coefficient of variation. N provides the number of observations used in each estimation.

Table 7
Robustness Checks

Panel A: Opposite-Sex Twins

Model	*N*	Variance Components		
		A - Share	*C* - Share	*E* - Share
Home Bias	7,916	0.462	0.012	0.526
		0.085	0.063	0.041
Turnover	7,412	0.279	0.000	0.721
		0.060	0.039	0.033
Disposition Effect	1,548	0.315	0.000	0.685
		0.087	0.052	0.056
Performance Chasing	4,390	0.326	0.089	0.584
		0.102	0.080	0.040
Skewness Preference	7,916	0.289	0.000	0.711
		0.056	0.036	0.036

Panel B: Model Misspecification

Model	*N*	Variance Components		
		A - Share	*C* - Share	*E* - Share
Home Bias	12,378	0.509	-0.047	0.538
		0.102	0.072	0.042
Turnover	11,508	0.354	-0.076	0.722
		0.077	0.051	0.033
Disposition Effect	2,268	0.365	-0.054	0.689
		0.150	0.104	0.060
Skewness Preference	12,378	0.331	-0.039	0.708
		0.102	0.071	0.041

Panel C: Excluding Similar Portfolios

Model	*N*	Variance Components *A* - Share	*C* - Share	*E* - Share
Home Bias	9,902	0.235	0.000	0.765
		0.058	0.025	0.043
Turnover	8,990	0.217	0.000	0.783
		0.044	0.021	0.033
Disposition Effect	1,714	0.110	0.029	0.861
		0.087	0.047	0.061
Performance Chasing	5,208	0.199	0.062	0.739
		0.088	0.061	0.040
Skewness Preference	9,902	0.120	0.053	0.827
		0.068	0.052	0.032

Panel D: Controlling for Social Interaction

Model	*N*	Variance Components *A* - Share	*C* - Share	*E* - Share
Home Bias	6,228	0.321	0.093	0.586
		0.123	0.096	0.046
Turnover	5,836	0.208	0.052	0.739
		0.085	0.063	0.037
Disposition Effect	1,192	0.233	0.046	0.721
		0.121	0.080	0.070
Performance Chasing	3,516	0.066	0.309	0.625
		0.094	0.079	0.039
Skewness Preference	6,228	0.152	0.123	0.725
		0.106	0.090	0.039

Table 7 reports results from maximum likelihood estimation for financial behaviors measured on direct stock holdings only. The different Financial Behaviors are modeled as linear functions of observable socioeconomic variables (see Table 2 for a list of the variables included) 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 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). 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 in case the shared environmental component 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. In Panel D, twin pairs are sorted into ten bins based on contact frequency between them (contact frequency ranges from zero to 360 times per year). By randomly dropping identical or fraternal twins, we ensure that each bin has the same number of identical and fraternal twin pairs. All variables are defined in Appendix Table A1. *N* provides the number of observations used in each estimation.

Table 8
Gene-Environment Interactions: Educaiton

	Home Bias		Turnover		Disposition Effect		Performance Chasing		Skewness Preference	
	Estimate	s.e.	Estimate	s.e.	Estimate	s.e.	Estimate	s.e.	Estimate	s.e.
Education										
a_m	0.2300	0.010	-0.2340	0.010	-0.2370	0.020	-0.2280	0.013	0.2300	0.010
c_m	0.1560	0.012	0.1520	0.013	0.1360	0.029	0.1440	0.017	0.1560	0.012
e_m	0.1820	0.004	0.1800	0.004	0.1710	0.008	0.1780	0.006	0.1820	0.004
Financial Behavior										
a_c	-0.0070	0.037	-0.0370	0.031	-0.1440	0.181	0.1090	0.035	-0.0030	0.009
alpha_c	-0.0010	0.031	0.0210	0.024	0.1320	0.138	-0.0720	0.027	0.0000	0.006
a_u	0.0500	0.061	0.0550	0.054	-0.0990	0.195	-0.0070	0.100	0.0280	0.008
alpha_u	0.0230	0.058	0.0100	0.032	-0.0890	0.143	-0.0330	0.075	0.0050	0.007
c_c	0.0120	0.036	0.0210	0.035	-0.1070	0.232	0.1240	0.038	0.0120	0.010
chi_c	-0.0120	0.031	-0.0230	0.026	0.1050	0.167	-0.0940	0.028	-0.0080	0.007
c_u	0.0580	0.045	0.0700	0.043	0.0560	1.221	-0.0700	0.062	0.0000	0.020
chi_u	-0.0570	0.031	0.0000	0.027	-0.0370	0.810	-0.0040	0.049	0.0000	0.010
e_c	-0.0040	0.020	-0.0110	0.024	-0.0910	0.110	0.0090	0.029	0.0020	0.007
epsilon_c	0.0000	0.017	0.0060	0.020	0.0750	0.088	-0.0030	0.024	0.0000	0.005
e_u	-0.0950	0.013	0.2010	0.013	0.5460	0.061	0.2250	0.017	0.0740	0.004
epsilon_u	-0.0270	0.011	0.0650	0.011	-0.1670	0.049	-0.0400	0.014	0.0030	0.003
N	6,804		6,348		1,304		3,494		6,804	

Table 8 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). All measures of biases are based on direct stock holdings only. In a first stage (untabulated), we have removed (via linear regression) the effect of control variables listed in Table 2, with the exception of those related to education. *N* provides the number of observations.

Table 9
Occupational Financial Experience

		Variance Components		
Model	*N*	*A* - Share	*C* - Share	*E* - Share
Diversification	622	0.000	0.222	0.778
		0.104	0.090	0.069
Home Bias	622	0.000	0.206	0.794
		0.088	0.082	0.073
Turnover	582	0.000	0.110	0.890
		0.106	0.067	0.088
Performance Chasing	562	0.026	0.106	0.868
		0.102	0.068	0.078
Skewness Preference	622	0.187	0.000	0.813
		0.091	0.042	0.079

Table 9 reports results from maximum likelihood estimation for subsets of twins that have occupational experience in finance. The different Financial 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 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).Financial behaviors are derived from all holdings of stocks and equity mutual funds. All variables are defined in Appendix Table A1. R^2 denotes the coefficient of variation. *N* provides the number of observations used in each estimation.

Table 10
Genetic Correlations

	Model I		Model II	
	Home Bias	Distance to Birthplace	Home Bias	Spouse from Home Region
A - Share	0.455	0.400	0.364	0.146
	0.059	0.085	0.116	0.092
C - Share	0.000	0.210	0.000	0.192
	0.039	0.061	0.066	0.067
E - Share	0.545	0.389	0.636	0.662
	0.031	0.036	0.081	0.041
Correlation	-0.031		0.010	
	0.009		0.022	
Genetic Correlation	-0.106		0.240	
	0.036		0.239	
Correlation of Common Environment	0.000		0.000	
Correlation of Individual Environment	0.031		-0.069	
	0.021		0.035	
N	12,180		2,566	

Table 10 reports results from maximum likelihood estimation of bivariate model. *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 2 for a list of socioeconomic variables included) as well as three 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 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 at least A, *C*, or *E* Share 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.

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	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.
Loss Aversion	We measure the Disposition Effect as the difference between the ratio of realized to unrealized gains and the ratio of realized to unrealized losses (see Odean (1998) and Dhar and Zhou (2006)). Securities are classified as losses and gains based on the raw return during a given year. We categorize gains and losses as realized if the number of units held decreases relative to the previous year, and unrealized otherwise. Finally, using all years with at least one sales transaction, we count for each investor the total number of realized and unrealized gains and losses. The Disposition Effect is then the difference between the ratio of realized to unrealized gains and the ratio of realized to unrealized losses.
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 that has purchased securities during our sample periods, we calculate performance chasing as 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.
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 averaged over all years with portfolio data.
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	The number of years of education based on the highest completed degree. The variable is obtained from the Swedish Twin Registry and available only for a subset of twins.
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.

Variable	Description
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).
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 (km)	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.

Figure 1
Correlations by Genetic Similarity

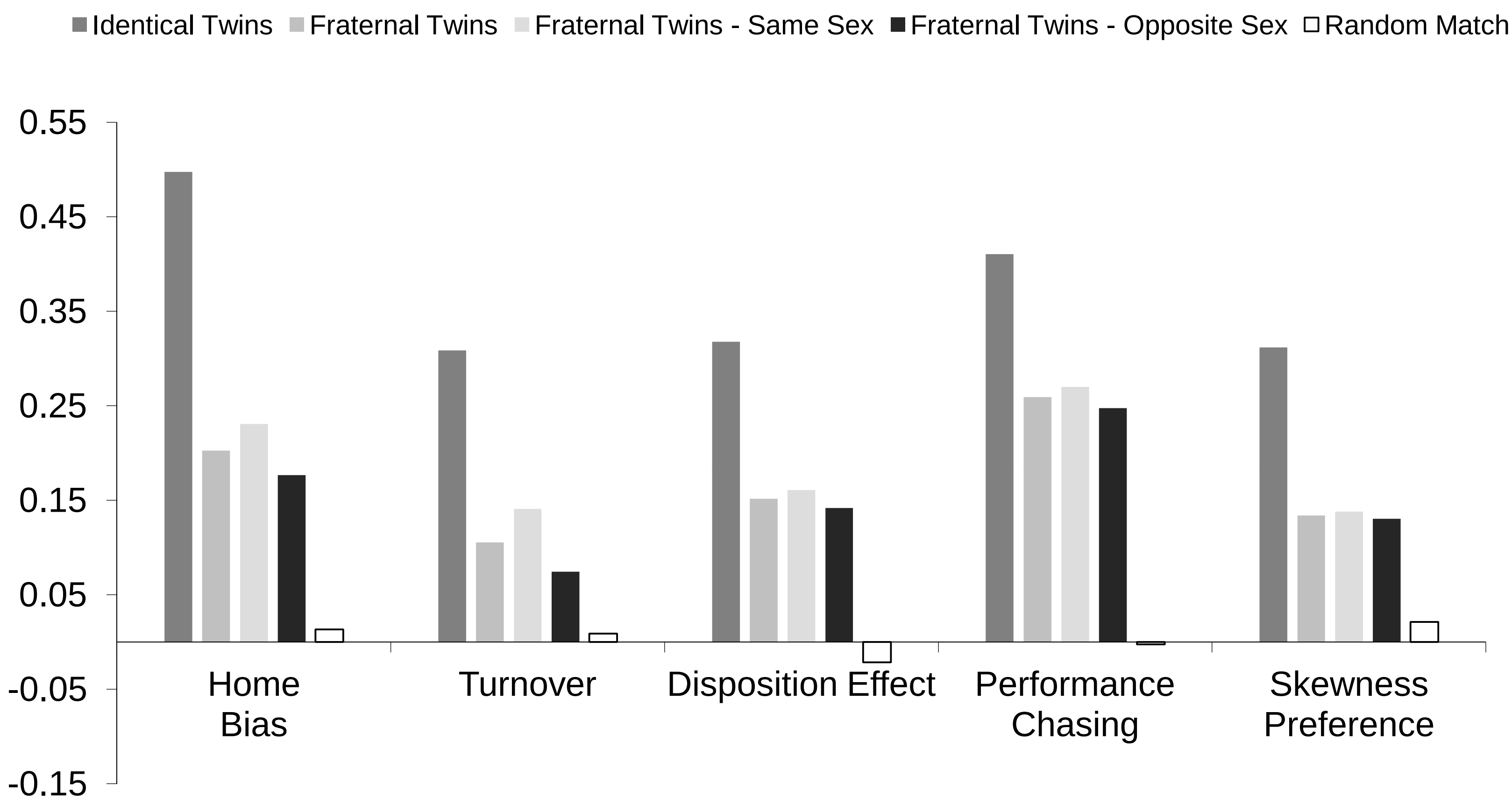

Figure 1 repots Pearson correlation coefficients for *Home Bias*, *Loss Aversion*, *Performance Chasing,* and *Turnover* between twins for different types of twin pairs as well as for twins randomly matched with non-twins controlling for age and gender. Measure are calculate using holdings and transactions of direct stock holdings only. All variables are defined in Appendix Table A1.

Figure 2
Gene-Environment Interaction

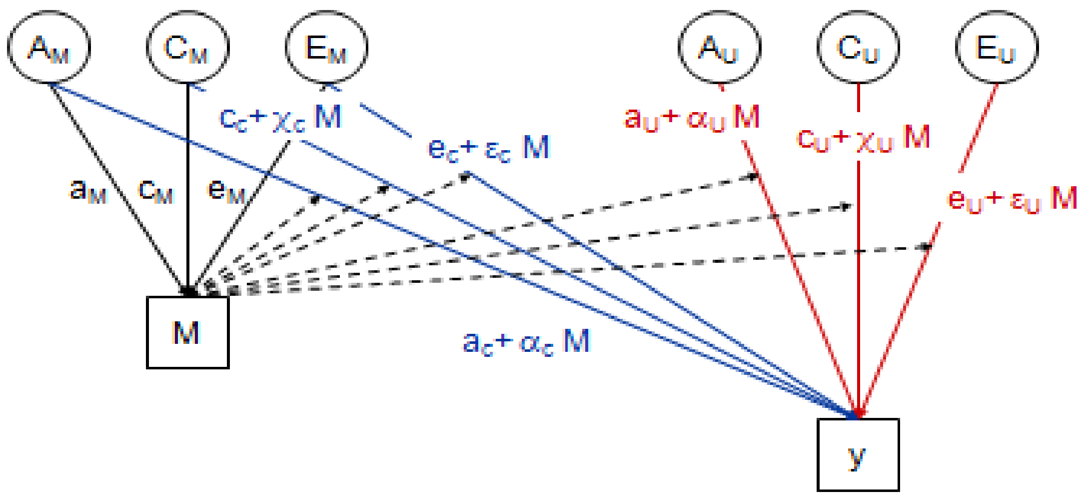

Figure 3

Education as a Moderator

Figure A: Home Bias

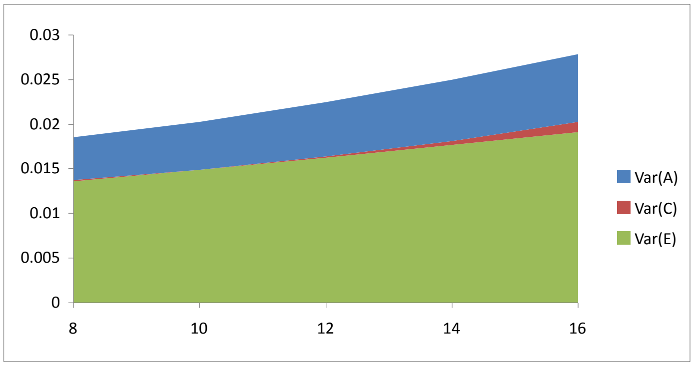

Figure B: Turnover

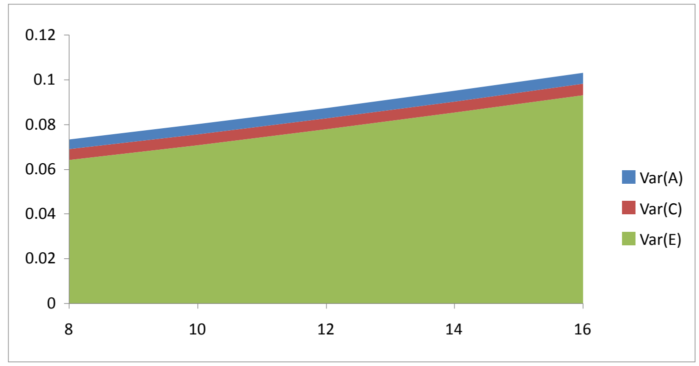

Figure C: Disposition Effect

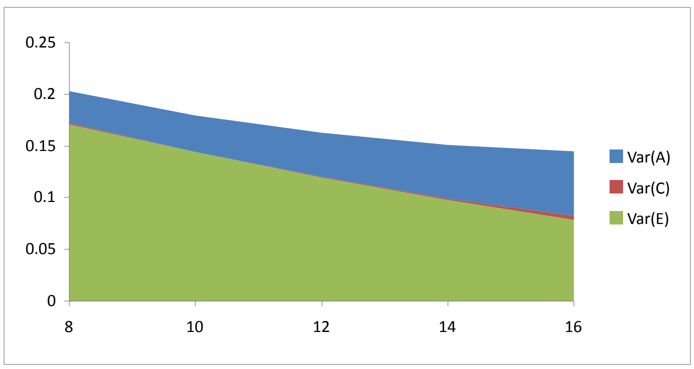

Figure D: Performance Chasing

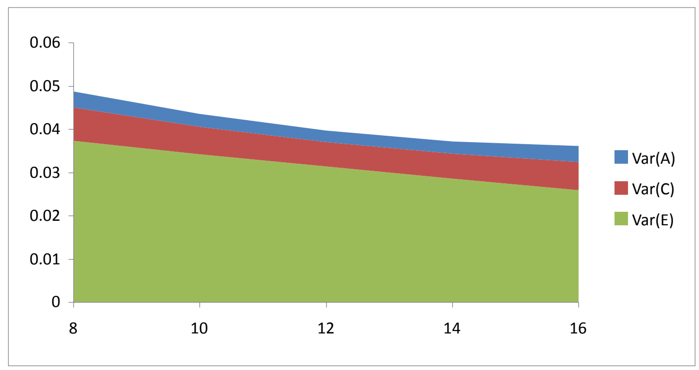

Figure E: Skewness Preference

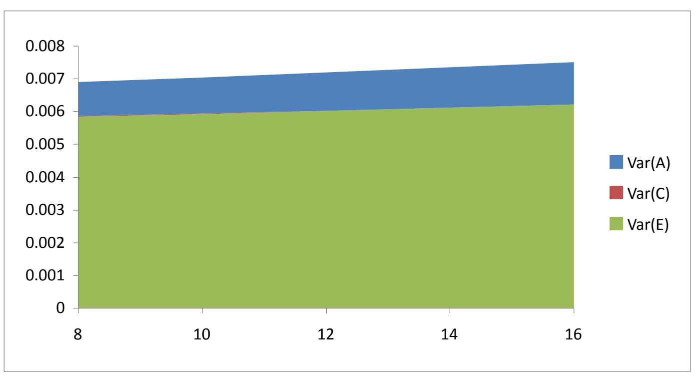

Figure 3 presents results of the gene-interaction model proposed by Purcell (2002). In each of the four panels, *Education* acts as the moderator. The *x*-axis represents years of education, while the *y*-axis represents the variance. See Table 8 for detailed estimation results.