Nature or Nurture: What Determines Investor Behavior?*

Amir Barnea, Henrik Cronqvist, and Stephan Siegel†

First version: July 9, 2009
This version: September 15, 2009

Abstract

We examine the foundations of investor behavior. Using data on identical and non-identical twins, matched with their complete portfolios, we decompose the cross-sectional heterogeneity in key measures of investment behavior into genetic and environmental influences. We find that up to 45 percent of the variation in stock market participation, asset allocation, and portfolio risk choices is explained by a genetic component. Genetic variation is a very important explanation for variation in investment behavior compared to the influence of education, net worth, entrepreneurial activity, and other factors studied in existing work. Furthermore, the family environment is found to have an effect on young individuals' portfolios, but in contrast to the genetic effect, it disappears with age as an individual acquires own experiences. Frequent contact between individuals leads to a common effect on investment behavior beyond the genetic factor. Finally, we find that twins who were reared apart still have similar portfolios.

*We thank seminar participants at the University of British Columbia, University of Washington, and Adlai Fisher, Todd Gormley, Avi Kamara, Jonathan Karpoff, Ed Rice, and Ingrid Werner for valuable comments and suggestions. We are thankful to Jack Goldberg and Eric Strachan at the University of Washington Twin Registry for advice. We thank Caroline Larsson and Peter Öberg (Statistics Sweden), Rozita Broumandi and Paul Lichtenstein (Swedish Twin Registry), Fredrik Hård af Segerstad (Swedish Investment Fund Association), Hans Linder (Euroclear Sweden), and Lance Risi (S&P) for assistance with the data compilation. We thank Hannah Gregg and Lew Thorson for outstanding research assistance. We want to acknowledge generous research funding from the Financial Economics Institute and the Lowe Institute of Political Economy at Claremont McKenna College (Barnea and Cronqvist), and the Global Business Center and the CFO Forum at the University of Washington (Siegel). The Swedish Twin Registry 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). This project was pursued in part when Cronqvist was visiting the Swedish Institute for Financial Research (SIFR), which he thanks for its hospitality. The project has been reviewed by the Swedish Twin Registry (submitted 12/31/2007, approved 3/14/2008), the Ethics Review Board for the Stockholm region (submitted 10/24/2008, approved 11/26/2008), and Statistics Sweden (submitted 11/20/2008, approved 3/3/2009). Any errors or omissions are our own.

†Barnea: Claremont McKenna College, Robert Day School of Economics and Finance (amir.barnea@cmc.edu); Cronqvist: Claremont McKenna College, Robert Day School of Economics and Finance (hcronqvist@cmc.edu); Siegel: University of Washington, Michael G. Foster School of Business (ss1110@u.washington.edu).

A devil, a born devil, on whose nature

Nurture can never stick; on whom my pains,

Humanely taken, all, all lost, quite lost ...

– Prospero speaking of Caliban in Shakespeare's *The Tempest*, 1611, IV.i.188-190

I Introduction

It is a well documented empirical fact in the finance literature that there is significant heterogeneity across individuals in terms of investment decisions and financial risk-taking behavior.[1] However, little is known about the foundations of this heterogeneity. Are we biologically predisposed to certain behaviors and born with a fixed set of financial risk preferences inherited from our parents (and previous generations) through our genetic composition?[2] Or is our investment behavior to a significant extent shaped by environmental factors, such as the shared environment of family and parenting or the non-shared environment of individual-specific experiences? These questions are fundamental for our understanding of investor behavior, but existing research has not offered systematic evidence on them. In this paper, we seek to fill this void by quantifying the extent to which "nature," i.e., genetic variation across investors, versus "nurture" or more generally environmental variation can explain the heterogeneity in investment decisions.

This study makes two main contributions to our understanding of investor behavior. First, our empirical approach enables us to test whether investment behavior is heritable. Recent work suggests that an individual might be predisposed to certain investment behaviors from birth on. For example, Sundén and Surette (1998) and Barber and Odean (2001) find gender-based differences in investment behavior: Men choose riskier portfolios and trade more than women.[3] However, from this evidence it is not possible to infer whether gender is the only, or most important, genetic component of

[1]See, e.g., Campbell (2006) and Curcuru et al. (2009) for recent and extensive reviews of the literatures related to heterogeneity in investor behavior.

[2]There is a long-standing view in economics that preferences are at least partly genetic (e.g., Becker (1976). Robson (2001a)), and Robson (2001b) goes as far as stating that "[i]f preferences are significantly shaped by individual experiences, the changes needed in economic theory are profound" (p. 901). For early work in economics from a biological viewpoint, see Hirshleifer (1977).

[3]See Croson and Gneezy (2008) for a review of work in economics on gender differences in preferences.

investment behavior or if gender-related differences in investment behavior reflect genetic differences at all. Men and women could be treated differently when growing up, systematically affecting their behavior in financial markets. In this paper, we estimate whether the variation in financial behavior across individuals has a significant genetic component.

Second, we are also able to measure the contribution of environmental factors, such as individual experiences, the shared family environment or social interactions, to the observed investor heterogeneity, above and beyond genetic effects. Hong et al. (2004) study stock market participation and find that social investors are more likely to invest in the stock market compared to non-social investors.[4] While this evidence could support the presence of an environmental factor, several personality traits, such as extroversion, have been shown to have a significant genetic component (e.g., Lang et al. (1996)).[5] There is also evidence that an individual's past experiences, such as the Great Depression, may affect the individual's risk-taking behavior decades later (e.g., Malmendier and Nagel (2007)).[6] Our study quantifies the proportion of the variation in investment behavior caused by differences in the shared and non-shared environment controlling for genetic effects.

To decompose the heterogeneity in three measures of investment behavior – stock market participation, asset allocation, and portfolio risk – into genetic and environmental components, we examine the behavior of identical and non-identical twins. The intuition of our identification strategy is straightforward. If individuals who are more closely related genetically (e.g., identical twins) tend to be more similar on an analyzed trait (e.g., the asset allocation), then this is evidence for that trait being heritable. Using data on twins allows us to identify a latent genetic factor as well as environmental components that are either common (i.e., shared) or non-shared among twins.

Our data on close to 40,000 twins are from the Swedish Twin Registry, which manages and maintains the world's largest database of twins. Until the abolishment of the wealth tax in Sweden

[4] For evidence on "peer effects" in the context of financial decisions, see also Madrian and Shea (2000), Duflo and Saez (2002), and Brown et al. (2008)).

[5] There are similar challenges of inferring genetic versus environmental effects in other studies of individual investor behavior. For example, Kumar (2009) finds that investors characterized by a preference for gambling prefer "lottery stocks." Such behavior may stem from the environment (e.g., relocation to Las Vegas and an adoption of gambling preferences), or a genetic propensity to gamble, which has been found by, e.g., Ibáñez et al. (2003).

[6] There also exists related evidence in corporate finance research which shows that experiences of the Depression-era among executives can influence the financial policies of the corporations they manage (Graham and Narasimhan, 2004).

in 2006, the law required all financial institutions to report information to the Swedish Tax Agency about the assets an individual owned as of December 31 of that year, which enables us to compile a matched data set of twins and their portfolios.[7]

Our empirical evidence shows that up to 45% of the overall heterogeneity in investment behavior is explained by a latent genetic factor. This result is robust to controlling for confounding factors such as age, education, net-worth, and entrepreneurial activity. We also demonstrate that the genetic component does not disappear with age and acquisition of individual experiences, is significant regardless of the intensity of twin contact, and accounts for a substantial proportion of the heterogeneity also among pairs of twins who were reared apart. While our evidence implies that nature is an important determinant of an individual's investment behavior, our analysis also demonstrates considerable environmental influences. In particular, twin correlations for the investment behaviors studied are less than one, although identical twins are genetically identical. Our evidence indicates that, for the most part, environmental influences that contribute to heterogeneity in financial behavior are those that make family members different, not similar. The family environment has an effect on the investment decisions of young individuals, but this effect is not long-lasting (unless twins have frequent contact) as it disappears as an individual acquires own experiences relevant for decision-making in the financial domain.

This paper is related to work on the cross-sectional variation in asset allocation. Early models such as Samuelson (1969) and Merton (1969, 1971) show that in frictionless markets, differences in preferences (risk aversion) are the only relevant source of heterogeneity.[8] To improve our understanding of portfolio choices, financial economists have more recently considered idiosyncratic income risk, entrepreneurial risk, and life cycle effects.[9] However, the explanatory power with respect to investment behavior such as asset allocation has remained disappointingly low, leaving most of the cross-sectional variation unexplained. For example, the adjusted R^2 is only 2-3 percent in most asset allocation studies (for a recent example, see, e.g., Brunnermier and Nagel (2008)). Our evidence shows that a genetic component significantly improves our understanding of investor

[7]Data on twins have previously been used in economic research, for example, to estimate the returns to schooling (Ashenfelter and Krueger (1994) and Ashenfelter and Rouse (1998)).

[8]For survey-based evidence of significant variation in individuals' risk preferences, see Barsky et al. (1997).

[9]See, e.g., Heaton and Lucas (2000), Vissing-Jørgensen (2002a), and Ameriks and Zeldes (2004).

heterogeneity.

Our study is also related to work in behavioral genetics. Starting with Loehlin and Nichols (1976), twin researchers have examined the genetic basis of complex personality traits, and found significant heritability of, e.g., the "Big Five" personality traits (e.g., Bouchard et al. (1990)).[10] Cesarini et al. (2009a) use twin data to provide evidence on the genetic component of altruism and risk taking. Differently from our study, they use a small sample of 920 twins, 80 percent of which are women who participate in experimental sessions. We study actual investor behavior, i.e., the propensity to invest in the stock market and the risk of an investor's investment portfolio for a large sample of twins using data on twins' complete investment portfolios. This is important as eliciting risk preferences using laboratory experiments does not always provide a reliable measure of risk preferences.[11] Finally, Kuhnen and Chiao (2009) use gene-mapping to explain differences in risk-taking behavior by the presence of specific genes.[12] Their evidence is key for our study, as it provides the neural foundations for genetic influence on risk-taking behavior. Differently from their paper, our focus is on quantifying the relative importance of genetic and environmental components for actual investment behavior.

In an independent and contemporaneous study of Swedish twins, Cesarini et al. (2009b) examine self-directed pension accounts in which individuals allocate 2.5%, up to a cap, of their labor income to five mutual funds. Since the program was introduced in 2000, the value of the funds at risk is small. Our data, on the other hand, characterize an individual's overall financial portfolio with an average market value of about $30,000. Most importantly, our main variable is the share of equities to all financial assets, a standard measure in portfolio choice models. In contrast, Cesarini et al. (2009b) focus on the return volatility averaged across the selected funds.[13] Furthermore, our study provides several distinct results. First, we show that while nurture plays an insignificant role on

[10]For a review of twins studies related to personality traits, see, e.g., Plomin and Caspi (1999).

[11]See Levitt and List (2007) for a general discussion of strengths of, and potential problems with, experimental approaches in economic research.

[12]Taking more risks may result in more or longer-lasting production of "feel-good" neurotransmitters, e.g., dopamine depending on an individual's genetic composition. Thus, risk taking may be experienced as more rewarding by individuals with specific genes.

[13]Specifically, Cesarini et al. (2009b) define their primary measure of portfolio risk as "the average risk level of the funds invested in by the individual, with the risk of each fund measured as the (annualized) standard deviation of the monthly rate of return over the previous three years" (p. 5).

average, it is very important for young investors. Second, we demonstrate how frequent contact between individuals leads to a common effect beyond a genetic factor. Finally, as it is difficult to identify genetic effects separately from shared environment effects using twin data, we study twins who were "reared apart" and find that there is still significant similarity in investment behavior, which strengthens our conclusion

The rest of the paper is organized as follows. Section II reviews the empirical research methodology we use to quantitatively decompose the variance in investment behavior into genetic and environmental components. Section III describes our data on twins and their investment portfolio, and defines the variables of interest. Section IV reports our results and robustness checks. Section V reports further evidence and extensions. Section VI concludes.

II Quantifying Genetic and Environmental Effects

In order to decompose the heterogeneity in investment behavior into genetic and environmental components, we investigate the behavior of pairs of identical and non-identical twins. If individuals who are more closely related genetically tend to be more similar on an analyzed behavior (e.g., the proportion of financial assets invested in risky assets), then this is evidence for that behavior being heritable, i.e., the behavior is at least partially affected by genes.

When a behavior is heritable, the correlation among identical twins is greater than the correlation among non-identical twins. Identical (monozygotic, MZ) twins share 100 percent of their genetic composition, while the average proportion of shared genes is only 50 percent for non-identical (dizygotic, DZ) twins. As we explain in more detail below, the identification strategy in this paper relies on these standard genetics facts.

We assume the following model for a measure of investment behavior (y):

$$y_{ij} = \beta_0 + \beta \mathbf{X}_{ij} + a_{ij} + c_i + e_{ij}, \tag{1}$$

where i indexes a twin pair and j (1 or 2) indexes one of the twins in a pair. β_0 is an intercept term and β measures the effects of the included covariates ($\mathbf{X}_{ij}$). a_{ij} and c_i are unobservable random effects, representing an additive genetic effect and the effect of the environment shared by both twins, respectively. e_{ij} is an individual-specific error term that represents the non-shared environment effects as well as any measurement error.[14]

The model assumes that a, c, and e (the subscripts are suppressed for convenience) are independently normally distributed with mean 0 and variance σ_a^2, σ_c^2, and σ_e^2, respectively, so that the residual (or unexplained) variance is the sum of three variance components, $\sigma_a^2 + \sigma_c^2 + \sigma_e^2$. Identification of σ_a^2 and σ_c^2 is possible because of the covariance structure implied by genetic theory. Consider two unrelated twin pairs $i = 1, 2$ with twins $j = 1, 2$ in each pair, where the first pair is of identical twins and the second pair is of non-identical twins. The corresponding genetic components are denoted $\mathbf{a} = (a_{11}, a_{21}, a_{12}, a_{22})'$. Analogously, the vectors of shared and non-shared environment effects are defined as $\mathbf{c} = (c_{11}, c_{21}, c_{12}, c_{22})'$ and $\mathbf{e} = (e_{11}, e_{21}, e_{12}, e_{22})'$, respectively. Assuming a linear relationship between gentic and behavioral similarity, genetic theory suggests the following covariance matrices:

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

The model described above is very similar to a general random effects model, with the difference being that the covariance matrices of the random effects in this case depend on the type of the twin pair (identical versus non-identical).

We use maximum likelihood estimation (MLE) to estimate the parameters of the model (see, e.g., McArdle and Pescott (2005) and Feng et al. (2009) for details). We also estimate the sum of the three variances σ_a^2, σ_c^2, and σ_e^2 as well as the proportion of the residual variance attributable to genetic effects, the shared environment, and the non-shared environment. For example, the

[14]The model discussed in this section is the most commonly used model in quantitative behavioral genetics research, and often referred to as an "ACE model." (A stands for additive genetic effects, C for shared (common) environment, and E for non-shared environment.)

proportion of the variance attributable to genetic influence, commonly referred to as heritability, is:

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

We compute the proportion of the variance attributable to σ_c^2 and σ_e^2 analogously. These three proportions, which we will generally refer to as the A, C, and E variance components are the estimates of main interest in this study.

We note that there are several simplifying assumptions behind this model.[15] First, we assume that all genetic effects are additive, i.e., a "dominant" gene is not important for the analyzed behavior. We consider the validity of this assumption in detail in our robustness check section. Second, we assume that heritability is the same in different environments, i.e., we assume the absence of gene-environment interactions. We will examine this assumption by estimating heritability for different age groups and by gender. Finally, we assume that the genetic effect and the effect of the shared environment are uncorrelated, i.e., identical and non-identical twins vary only in their genetic similarity, but not in the effect the shared environment has on them. If for example identical twins interact socially more than non-identical twins or if parents treat identical twins differently from non-identical twins, then this assumption may be violated and may result in an upward bias of the genetic component. We return to and address the validity of this assumption in our empirical analysis by explicitly controlling for twin contact intensity and by studying twins that were reared apart.

III Data

A The Swedish Twin Registry

We use data on twins from the Swedish Twin Registry (STR), managed and maintained by Karolinska Institutet in Stockholm, Sweden. The STR is the world's largest database of twins. The registry is compiled by the STR obtaining data on all twins' births from national databases of birth records in Sweden. The STR is recognized worldwide for the quality of its data, which have been used in a

[15]For a critical evaluation of twin research methodology, see, e.g., Goldberger (1977).

large number of published research papers in different fields.[16]

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 pair and twin identifiers and zygosity status,[17] 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. The participation rate in SALT, for the 1926-1958 cohort, was 74 percent. The participation rate in STAGE was also high, 60 percent, in spite of the fact that a very large number of questions (approximately 1,300) were asked. For further details about STR, we refer to Lichtenstein et al. (2006).

B Data on Twins

Table 1 reports summary statistics for our data set of twins. All data refer to the year 2002. The minimum age to be included in our sample is 18. We report summary statistics for "complete" twin pairs only, i.e., pairs for which both twins were alive in 2002, and for which data on individual portfolio choices are available.

Panel A shows the number of twins by type and gender. In total, there are 37,504 twins. Split by zygosity, we see that 10,842 (29%) are identical twins, while 26,662 (71%) are non-identical twins. That is, non-identical twins are more common than identical twins. Moreover, we see that opposite-sex twins is the most common twin type (38%), and identical male twins is the least common one (12%). The evidence in the table on the relative frequency of different types of twins is consistent with that from other studies which use large samples of twins.

Panel B reports summary statistics for the following individual characteristics: age, education,

[16]We examined the possibility of using data from a U.S. twin registry. The largest is the Mid-Atlantic Twin Registry (MATR) at the Virginia Commonwealth University with more than 37,000 twins of all ages who were born in or live in North Carolina, South Carolina, and Virginia. Other large U.S. twin registers used in twin research include the Minnesota Twin Family Study (MTFS) and the University of Washington Twin Registry. The problem with using these twin registries is that data on twins' individual portfolio choices are not available. We believe that Sweden is the only country where such a matching is feasible.

[17]Zygosity is based on questions about intrapair similarities in childhood. One of the survey questions is: 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? This method has been validated with DNA as having 98 percent or higher accuracy. For twin pairs for which DNA sampling has been conducted, zygosity status based on DNA analysis is used.

disposable income, net worth, and indicators for being a business owner or a home owner.[18] Definitions of all variables are available in the Appendix. We construct three education indicator variables based on an individual's highest level of education: less than nine years of schooling ($Education1$), high school ($Education2$), and college ($Education3$). *Disposable Income* is the disposable income of the individual's household. *Net Worth* is the difference between the market value of an individual's assets and liabilities. *Business Owner* is an indicator variable that equals one if an individual's income from active business activity is more than 50% of the individual's labor income, and zero otherwise. *Home Owner* is an indicator variable that equals one if the market value of owner occupied real estate is positive, and zero otherwise. Comparing identical and non-identical twins, we see that they are generally similar.

It is also interesting to compare the samples of twins to the population. In the table, we therefore report characteristics of a random sample of the same size (37,504 Swedish individuals) and with the same age distribution. We find that twins are similar to the population. That is, the sample of twins seems to generally be representative of the population in terms of individual characteristics.

C Data on Portfolio Choices

The data on individuals' portfolios are from the Swedish Tax Agency. Until 2006, households in Sweden were subject to a 1.5 percent wealth tax on asset ownership (other than ownership of a business which is not included in "taxable wealth") above a threshold of SEK 3 million (or about $343,000 at the exchange rate of 8.7413 Swedish krona per dollar as of 12/31/2002) for married tax filers and SEK 1,500,000 for single filers. When an asset is jointly owned by two or more tax filers, the market value is split between the tax filers.

Until the abolishment of the wealth tax, the law required all Swedish financial institutions to report information to the Tax Agency about the securities (including bank account balances) an individual owned as of December 31 of that year.[19] Statistics Sweden matched twins with their portfolios using *personnummer* (the equivalent to Social Security numbers in the U.S.) as the unique

[18] The size of the samples (N) differs across columns because of data availability.

[19] A comprehensive analysis of individual portfolio choice data from Sweden has recently been performed by Calvet et al. (2007, 2009).

individual identifier.

For each financial security owned by an individual, our data set contains data on both the number of securities and each security's International Security Identification Number (ISIN). We obtain daily return data for these assets from a large number of sources, including Bloomberg, Datastream, and the Swedish Investment Fund Association (Fondbolagens Förening).

Table 2 reports summary statistics for twins' portfolio choices. We split the twins by zygosity type in the first set of columns in the table. In the final set of columns, we report summary statistics for the random sample of 37,504 Swedish individuals. The average portfolio value of identical and non-identical twins is similar: $29,987 and $33,264, respectively.

In Panel A, we examine how their financial assets are allocated. We report the proportion of financial assets in cash (i.e., bank account balances and money market funds), bonds and fixed income securities, equities (direct versus funds), options, and "other financial assets."[20] Cash is the most common asset in the portfolios (42% and 43% for identical and non-identical twins), followed by stock funds which at the mean constitute 35% and 33% for identical and non-identical twins, and then direct ownership of stocks (12% for both identical and non-identical twins). We find that the compositions of twins' portfolios are generally very similar to those in the random sample.

In Panel B, we report summary statistics for the measures of investment and risk-taking behavior in financial markets which we will analyze. *Stock Market Participant* is an indicator variable that is one if the investor holds any investment in equities, and zero otherwise. *Shares in Equities* is the proportion of financial assets invested in equities conditional on being a stock market participant.[21] We use this measure because of its theoretical relation with an individual's risk aversion coefficient (γ). In a simple asset pricing model, assuming constant relative risk aversion (CRRA) and independently and identically distributed asset returns, it can be shown that $1/\gamma_i$ for individual i is proportional to the proportion that the individual invests in risky assets. That is, the genetic component of the proportion of risky assets is a measure of the percentage of an investor's risk aversion coefficient that

[20]Cash in bank accounts with a balance of less than SEK 10,000 (or for which the interest was less than SEK 100 during the year). However, Statistics Sweden's estimations suggest that 98 percent of all cash in bank accounts is included in the data. The class called "other financial assets" includes rights, convertibles, and warrants.

[21]Note that the sum of the "Proportion of financial assets in equities (direct)" and the "Proportion of financial assets in equities (funds)," in Panel A is not equal to *Share in Equities* in Panel B because of the conditioning on stock market participation in Panel B.

can be explained by genes. We also consider a "model-independent" measure of financial risk-taking behavior: *Volatility*, the annualized daily time-series volatility of an investor's equity portfolio.

We find that the twins are very similar on the measures of investment behavior reported in the table: 80 (78) percent of identical (non-identical) twins invest in the stock market.[22] At the mean, *Shares in Equities* are 59 and 57 percent, respectively, for identical and non-identical twins. The annualized volatility is 18 percent, on average, for both identical and non-identical twins. Finally, the table shows that the means for our sample of twins are generally within a few percentage points of the means of the random sample.

IV Empirical Results

A Identical and Non-Identical Twin Pair Correlations

We start our empirical analysis by reporting separate Pearson's correlation coefficients for identical and non-identical twin pairs for the three measures of investment and risk-taking behavior studied in this paper: *Stock Market Participant*, *Share in Equities*, and *Volatility.* These correlations will provide a first and intuitive indication of whether financial behavior seems to have a genetic component. For non-identical twins, we report correlations for both same-sex and opposite-sex twins. Finally, as a comparison, we also report the correlations between twins and randomly selected individuals from the population, that were matched based on age.[23] The correlations involving random matches are expected to be significantly lower than the correlations among identical and non-identical twin pairs as they only capture age effects in investment behavior.

Figure 1 shows the correlation results. There are three important conclusions that can be drawn from the figure. First, for each measure, we find that the correlation is substantially greater for identical twins than for non-identical twins, indicating a substantial genetic component for all the measures studied. These differences are found to be statistically significant at the 1%-level. For *Stock Market Participant*, the correlation among pairs of identical twins is 0.298, compared to only

[22]Relative to the U.S., stock market participation is high in Sweden (e.g., Guiso et al. (2002)).

[23]Specifically, for each twin in our data set, we randomly select a non-twin of the exact same age from the Swedish population. This individual constitutes the twin's "random match pair." We then compute the correlation between the twin and her random match pair.

0.143 for non-identical twins. For *Share in Equities*, the finding is similar: the correlation among identical twins is 0.307, significantly higher than the correlation among non-identical twin pairs, which is only 0.150. Finally, for *Volatility* we find that the correlation for identical twins is 0.394, compared to 0.181 for non-identical twins.

Second, for non-identical twins, the correlations are greater for same-sex twins compared to opposite-sex twins. The p-values for statistically significant differences are 0.005, 0.674, and 0.000, respectively, for *Stock Market Participant*, *Share in Equities*, and *Volatility*. Our interpretation of the higher correlations for same-sex twins is that gender-based differences are present in the investment behaviors studied. These results are related to the findings by Sundén and Surette (1998) and Barber and Odean (2001), who were first to document that there are significant gender-based differences in portfolio risk and trading. Our results suggest that gender differences extend to a wider range of financial behaviors. Because of these gender differences, we will include gender as a covariate in our formal statistical analysis.

Finally, the correlation between twins and randomly drawn individuals of the same age from the population is significantly lower than the correlations among identical or non-identical twin pairs. On average, these correlations are only 0.020. The slight positive correlation may be explained by age effects in portfolio choices (e.g., Ameriks and Zeldes (2004)). That is, two randomly selected individuals of the same age have somewhat similar portfolio choices because of life-cycle effects in investment behavior. We will therefore include age and age-squared as covariates in our analysis.

The correlation results reported so far are an indication that the probability of investing in the stock market and the propensity to take on financial risk in one's investment portfolio is explained, at least in part, by a significant genetic factor. However, there is also evidence of environmental influences because identical twin correlations are considerably less than one. Next, we therefore estimate the relative importance of genes and different environmental factors.

B Decomposing the Cross-Sectional Variance of Investment Behavior

B.1 Estimates from Random Effects Models

As described in Section II, we can decompose the variance in each of the measures of investment and risk-taking behavior into three components: an additive genetic component (A), an environmental component (C), which is shared by both twins, for example their upbringing, and a non-shared environmental component (E).

Table 3 reports the estimates from the maximum likelihood estimation, with one measure in each panel. We estimate the parameters of the model specification in equation (1), controlling for $Male$, *Age*, and *Age-squared*, because of the age and gender-based effects in financial behavior noted above. This allows us to estimate the proportion of the residual variance attributable to the three components, A, C, and E. For example, for A the table reports $\sigma_a^2/(\sigma_a^2 + \sigma_c^2 + \sigma_e^2)$, the proportion of the total variance attributable to a genetic factor. We compute the proportion of the variance attributable to C and E analogously. The first row of each panel reports an E model, in which the additive genetic effect and the effect of the shared environment are constrained to zero. The second row reports a CE model, in which the additive genetic effect is constrained to zero and the final row reports the full ACE model. To enable comparisons of model fit across models, we also report the Akaike Information Criterion (AIC) for each model.

We draw three conclusions from the table. First, when we compare the fit of the estimated models (E versus CE versus ACE models) we find that the ACE model is always preferred based on the AIC, i.e., the ACE model has the lowest AIC. We also compute the χ^2 from likelihood ratio (LR) tests and find that in all cases at the 1%-level the E model is rejected in favor of a CE model, which in turn is rejected in favor of an ACE model (untabulated). That is, including a latent genetic factor is important if we want to understand and explain the cross-sectional heterogeneity in investor behavior and risk-taking in financial markets.

Second, we find that the genetic component, A, of investment and financial risk-taking behavior is statistically significant and that the magnitude of the estimated effect is large. That is, we discover a substantial genetic component across all of the financial behaviors studied. For *Stock Market Participant* (Panel A), the estimate of A is 0.287, and statistically significant at the 1%-level. For

Share in Equities (Panel B), the genetic component is 0.283. In a simple asset pricing model, the genetic component of the proportion risky assets is a measure of the proportion of the variation in investors' risk aversion that can be explained by genes and not the environment because γ_i is inversely proportional to investor i's proportion invested in risky assets. Thus, one interpretation of our results is that about 28% of the total variance in risk aversion across individual investors is attributable to a genetic factor. This finding supports the long-standing view in economics that preferences are at least partly genetic (e.g., Becker (1976) and Robson (2001a, 2001b)).

We also consider a measure of risk-taking in financial markets that is model-independent: *Volatility* measured as the annualized daily time-series volatility of an investor's equity portfolio. We analyze this measure in Panel C of Table 3 and find that genes are again important, as the estimate of A is 0.370.

We find that the shared environmental factor, C, is estimated to be zero for all three measures of financial behavior. This suggests that on average differences in "nurture," i.e. the common environment twins grew up in, or differences in the common environment twins share as adults, do not contribute to explaining differences in the observed investment behavior. For example, parents do not seem to impact their children's decision to invest or not invest in the stock market, above and beyond the genetic transmission channel. This suggests that the intergenerational correlation of the propensity to invest in the stock market reported by Charles and Hurst (2003) is due to genetic similarity, but not due to the family environment in which children grow up in or other non-genetic sources that would affect all twins in the same way. This result is somewhat surprising as the family environment constitutes a natural source of information which could allow children to overcome fixed participation costs.[24] While parents have a significant impact on their children's asset allocation and the riskiness of chosen portfolios, this influence is found to be through their genes and not parenting or other non-genetic sources.

Finally, we find that the non-shared environment, i.e., the individual experiences and non-genetic circumstances of one twin that are not equally shared with the other twin, contribute substantially

[24] Vissing-Jørgensen (2002b) develops a model in which fixed costs of participation are incurred in each period, and estimates that such costs have to be about $200 per year to explain the stock market participation rate observed in the U.S.

to the observed heterogeneity. For *Stock Market Participant*, the non-shared component (E) is 0.713. For *Share in Equities*, E is 0.718. The result is similar when we analyze *Volatility*: the non-shared component is 0.630.

B.2 Effects of Including Covariates

In order to contrast the importance of the latent genetic effect with the contribution of observable investor characteristics typically employed in empirical portfolio choice models, we re-estimate the random effects models with additional controls.

Table 4 reports the results for these specifications. In the section of the table entitled "Mean," we report the parameter estimates and standard errors for β_0 and β in equation (1), which measures the effects of the covariates on the mean of the measure studied. In the first column for each measure (columns I, III, and VI in the table), we do not include any covariates. In the following column for each measure (columns II, IV, and VII), we include $Male$, *Age*, and *Age-squared*, as well as the additional controls $Education1$, $Education2$, $Wealth$, *Business Owner*, and *Home Owner*.[25]

Because we observe *Share in Equities* and *Volatility* only for stock market participants, the coefficient estimates for those two measures could be biased due to sample selection. In the final column for these two measures (columns VI and VIII), we therefore report results from using Heckman's (1976) two-stage sample selection approach. In the first stage, we estimate a probit model for stock market participation. In addition to the controls used in the second stage, the probit specification also includes disposable income as an explanatory variable.

Focusing on columns II, V, and VIII, we find that men are more likely to invest in the stock market, invest a larger fraction of their financial assets in equities, and hold more volatile equity portfolios. Consistent with previous research, we find that *Stock Market Participant*, *Share in Equities*, and *Volatility* increase in educational achievement as well as net-worth. Business owners are more likely to invest in the stock market, but hold a smaller fraction of their financial assets in equities, while home ownership is positively associated with being an equity holder and investing

[25]We have also explored other sources of background risk. For example, Vissing-Jørgensen (2002a) examines the effect of labor income volatility on stock market participation and allocation. We find that the volatility of non-capital income growth, computed over the 1998-2006 panel for individuals with at least five data points, has an insignificant effect (untabulated).

in equities. Finally, we observe that the coefficients on the inverse Mill's ratio are statistically significant.

In the section of the table entitled "Residual Variance", we report the variance of the combined error term, i.e., we report the sum of σ_a^2, σ_c^2, and σ_e^2. In columns I, III, and VI, the residual variance equals the total variance of the dependent variable. To the extent that the explanatory variables explain the variation of the dependent variable, the residual variance decreases as explanatory variables are added. Examining the residual variances in columns II, V, and VIII, it is apparent that the explanatory power (measured as the reduction in the residual variance) of the included investor characteristics is small, ranging between 1.4% for *Stock Market Participant* and 3.6% for *Share in Equities*.[26]

Finally, the decomposition of the residual variance suggests that even after controlling for an extensive set of individual characteristics, we still find a significant genetic component. Across the financial risk-taking measures, the estimated A is about one third of the residual variance, varying from 0.293 to 0.380. That is, adding a large set of covariates which themselves might be heritable does not significantly alter our conclusions about the heritability of investment behavior.[27]

C Robustness

C.1 Measurement Error

Our conclusions so far of a significant idiosyncratic environmental factor influencing investment behavior is susceptible to the criticism that measurement error in y is absorbed by e. This could overstate the non-shared component, E, i.e., $\sigma_e^2/(\sigma_a^2+\sigma_c^2+\sigma_e^2)$. First, as our portfolio data originate from the Swedish Tax Agency and misreporting of security ownership by financial institutions

[26]We use a linear probability model to model the binary choice whether to participate in the stock market. The *Pseudo*-R^2 from a probit model with the same explanatory variables is 16% which corresponds better to the consensus in the literature that entry costs are indeed an important explanation of the observed variation in stock market participation. The low explanatory power we report with respect to *Share in Equities*, on the other hand, is consistent with largely unexplained variation reported in other recent studies. For example, Heaton and Lucas (2000) report an adjusted R^2 of 3%, while Brunnermier and Nagel (2008) report an adjusted R^2 of 2%. Higher R^2 are typically observed only when a lagged dependent variable is included.

[27]See, for example, Björklund et al. (2006) for evidence on heritability of educational achievement.

and/or individuals is prosecuted, we consider measurement errors to be infrequent in our data set.[28]

Second, it is also possible that idiosyncratic shocks combined with transaction costs constrain individuals from rebalancing their portfolios to the optimum each year. In Panel A of Table 5, we therefore re-estimate the ACE models for each of the three measures of investment and risk-taking behavior using averages from the time-series rather than measures from 2002. The E component declines when we use time-series averages. Correspondingly, the A component increases by 0.067-0.093 depending on measure when time-series averages are used. That is, measurement error may cause a downward bias of the previously estimated genetic component.

C.2 Model Specification

The empirical analysis so far has assumed an additive genetic component. However, it is possible that there is a dominant genetic effect as well. This can be thought of as a non-linearity of the genetic effect. When the identical twin correlation is more than twice the non-identical twin correlation, one potential explanation is that a dominant gene influences that behavior. This is the case for some of the correlation comparisons reported in the paper.

A dominant genetic effect can be added in a straightforward way to the model described in Section II. While a model with A, C, E components and also a D component is not identified with our data, we are able to estimate an ADE model:

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

where the definitions are similar as previously. The corresponding genetic components are denoted

[28] We recognize that some degree of tax evasion is possible among the twins studied in this paper. For securities not to appear in our data, they have to be owned through a foreign financial institution which is not required by law to report information to the Swedish Tax Agency. The individual also has to misreport the ownership, and it has to remain undetected in spite of audits. In addition, financial institutions are required to report large withdrawals from bank accounts around December 31 (only relevant for individuals subject to the wealth tax and who would benefit financially from window-dressing the amounts of their total assets around December 31).

$\mathbf{d} = (d_{11}, d_{21}, d_{12}, d_{22})'$. Genetics theory suggests the following covariance matrix:

$$\text{Cov}(\mathbf{d}) = \sigma_d^2 \begin{bmatrix} 1 & 1 & 0 & 0 \\ 1 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1/4 \\ 0 & 0 & 1/4 & 1 \end{bmatrix}.$$

Panel B of Table 5 shows that D, i.e., $\sigma_d^2/(\sigma_a^2 + \sigma_d^2 + \sigma_e^2)$, is 0.075, 0.061, and 0.079, respectively, for *Stock Market Participant*, *Share in Equities*, and *Volatility*. However, only one of these estimates is statistically significant at the 10%-level. Given that the C component is zero in all previous model specifications, it is not surprising that the total genetic component ($A+D$) in the table approximates the previously estimated A component. That is, our conclusions regarding the importance of a genetic component of financial behavior does not change when modeling a non-linear genetic effect.

V Further Evidence and Extensions

In this section, we provide further evidence on the importance of genetic and environmental effects for investment behavior. We focus on *Share in Equities* as our measure of investment behavior because of the measure's central role in the empirical portfolio choice literature.

A Differences across Age Groups and Gender

We first turn to an analysis of whether the relative importance of genetic and environmental influences on investment behavior vary with age and gender. We start by separately considering the youngest ($Age < 30$) and oldest ($Age \geq 80$) individuals in our sample. We also consider the two in-between groups spanning 25 years each, i.e., 30-54 and 55-79 year old individuals, respectively.

Figure 2 reports the correlations among pairs of identical and non-identical twins for asset allocation across age groups. We find that the correlations for identical twins are higher than for non-identical twins regardless of age group. This is not surprising given our previously reported results of a significant genetic component affecting financial behavior. However, we find that both correlations decrease significantly as an individual ages. The decline is particularly pronounced around the age of 30, indicating that this is a particularly defining period for financial behavior during the life-cycle. For the youngest investors, the MZ (DZ) correlation is found to be 0.641 (0.431), compared to 0.172 (0.082) for the oldest investors.

Panel A of Table 6 reports the variance components A, C, and E for different age groups. Figure 3 illustrates the evidence. The estimates come from separate models for the four age groups. We find that the genetic component decreases by about 63 percent (from 0.445 to 0.162) when comparing the youngest and the oldest investors. By far, the steepest incremental decline takes place during the early years. During the period before entering the labor market and early on during an individual's life, the genetic component seems to dominate, but as experiences are gained, they start to determine a relatively larger proportion of the variation in financial behavior across individuals.

While the importance of genes is found to decline as a function of age, it is interesting to note that genes are found to matter also for the financial behavior of the oldest individuals in our sample, i.e., those older than 80. As a matter of fact, the A component never attains zero, but remains statistically significant at the 1%-level. The decrease in the importance of the genetic component is significant during early years, but reaches a steady state level of about 20 percent already when an individual is in his or her 30's, after which the marginal decline is small. A certain component of an individual's financial behavior never disappears from the individual, despite the accumulation of other significant experiences during life.[29]

For those younger than 30 years old, we find that the shared environment component is 0.197, and statistically significant at the 1%-level. That is, about 20 percent of the cross-sectional variation in investment behavior among the youngest individuals in our sample is explained by the environment which is common to the twins. While the shared environment is not important for investment and financial risk-taking behavior when considering individuals of all ages, it is important for the youngest and least experienced investors. However, this influence of "nurture" decreases sharply, completely disappearing after age 30. This behavior stands in sharp contrast with the finding for

[29]There is evidence of substantial genetic influences on cognitive abilities (e.g., the speed of information processing) in twins 80 or more years old (McClearn et al., 1997).

the genetic component, which also declines dramatically, but which does not attain zero even for the oldest investors. The non-shared environment increases in importance as an individual acquires own experiences relevance for financial decision-making.

Finally, we turn to gender-based differences in heritability of behavior in the financial domain. Panel B of Table 6 reports the variance components A, C, and E separately for men and women. The number of observations is somewhat lower in this analysis as opposite-sex DZ twins are dropped. For men, the A component is 0.291, i.e. somewhat larger than for women for which it is 0.224. The C component is zero for men, but 0.053 for women, though it is not statistically significant. While men and women exhibit significantly different propensities to take on risk in their investment portfolios (men prefer more risk than women), the extent of heritability of these behaviors is similar across men and women.

We conclude that the sources of the heterogeneity in investment and financial risk-taking behavior across individuals vary across age groups. The relative importance of genetic composition and the shared environment is largest for younger individuals. Although both components decline in importance as a function of age, the genetic component never disappears completely, not even in those 80 or more years old. We also conclude that there is little systematic difference in the heritability of investment behavior between men and women, which suggests that gender differences in investment behavior are expected to persist.

B Effects of Contact Intensity

In the domain of investment and financial risk-taking behavior, there are several ways through which contact and social interaction can impact individuals' behavior. Through word-of-mouth, individuals may learn from each other (e.g., Bikhchandani et al. (1992) and Shiller (1995)).[30] Individuals may also derive utility from conversations about investments and stock market related events, the way they enjoy discussing restaurant choices in the Becker (1991) model.[31] This has two implications. First, distinguishing between twins that have little contact with one another and those that have lots

[30] For an extensive review of this literature, see Bikhchandani et al. (1998).

[31] Shiller and Pound (1989) report survey data related to information diffusion among stock-market investors by word-of-mouth.

of contact might allow us to better understand the importance of the environment shared between twins. Secondly, to the extent that identical twins have more contact than do non-identical twins, our estimation procedure could lead to an upward bias in the estimated heritability of financial behavior. In this section, we examine these implications.

We analyze data on twins' contact and meeting intensities from the surveys performed by the Swedish Twin Registry. Specifically, we examine twins' responses to two questions: (i) "How often do you have contact?" and (ii) "How often do you meet?" It is important to note that both the SALT and STAGE surveys were conducted around the same time as we observe the portfolio choice data meaning that responses reflect contemporaneous social interaction.

Table 7 reports results related to twin interactions. Panel A shows summary statistics for contact and meeting frequencies among the twins in our sample.[32] For contact and meeting frequencies, we find statistically significant differences. The mean number of twin pair contacts is 176 per year for identical twins, compared to 77 for non-identical twins. If we instead study the number of times twins meet, then the numbers are 93 per year for identical and 37 for non-identical twins. These differences are statistically significant at the 1%-level.[33] These significant differences in contact intensity emphasize the importance of the analysis we perform in this section.

Panel B reports results for different groups of twins based on how often they contact each other. For twins with little contact (less than 20 contacts per year, the 20th percentile), the genetic component (A) is 0.142, and statistically significant at the 1%-level. The shared and non-shared environmental components are zero and 0.858, respectively. Interestingly, twins who respond that they do not interact at all or who interact very little still share a significant component when it comes to financial decision-making, and this similarity is found to be caused by shared genes as opposed to a common environment. For twins who have lots of contact (more than 155 contacts per year, the 80th percentile), we find an A component of 0.238 and a C component of 0.128 which is statistically significant at the 1%-level. The E component is 0.634. That is, the social interaction appears to create a common environment that is causing similarity in terms of investment behavior.

[32] These measures are based on the average of what the twins in a pair responded in the surveys. Twins generally have a similar view of the frequency of their contacts. The twin pair correlation between responses for frequency of contact is 0.77.

[33] The correlation between contact and meeting frequencies is 0.64.

Figure 4 shows the estimated variance components for the three groups based on contact frequency. As can be seen in the figure, the genetic component is similar regardless of how often twins interact. The shared environment component increases dramatically if we compare twins with little contact to those who have a lot of contact. Turning to twin correlations, Figure 5 shows that twin pairs who interact more also have more similar asset allocations. The MZ (DZ) twin pair correlations are 0.187 (0.075) among twins with little contact. In contrast, the correlations are 0.377 (0.270) for identical (non-identical) twins with lots of contact.

The analysis of contact intensity results in two important conclusions. First, contact intensity and information sharing related to specific investments does not explain the genetic component of financial behavior. A significant genetic factor explains similarity in investment and financial risk-taking behavior even when we study those who have little contact. The evidence that twins who have little contact still display similar financial behavior, emphasizes our conclusion that individuals are biologically predisposed to certain behaviors in the financial domain.

Second, individuals who have lots of contact create their own shared environment, which in our formal statistical analysis is captured by the C component. For those with little contact, the shared environment can be thought of as their common parenting and family environment when growing up, but those with frequent contact create a common environment as they stay in contact even after separating from their parents. Although not as important as the genetic component, our results do indicate that information diffusion among individuals is a significant explanation for heterogeneity in investor behavior among those with very frequent contact. This finding is related to Hong et al. (2004) who show that social investors are more likely to invest in the stock market relative to non-social investors. They use survey data from the Health and Retirement Study (HRS) in the U.S. and define social interaction based on whether individuals responded that they know their neighbors or attend church. Differently from Hong et al. (2004), we are able to compare the portfolios of two individuals as a function of twin-pair-specific contact intensity.

C Evidence from Twins Reared Apart

If parents treat identical twins differently from non-identical twins, then the genetic component (A) and the shared environmental component (C) may be confounded, i.e., the estimate of A could be upward biased. In an attempt to remedy such concerns and separate these two effects, we also study twins who were "reared apart," i.e., twins who were separated soon after birth and who therefore were exposed to no (or very limited) common family environment (e.g., Bouchard et al. (1990)).[34]

Ethical considerations by adoption authorities in Sweden mean that it is uncommon that twins are split up at or around birth. Still, we are able to identify a small sample of twins who were reared apart by their responses to two question in the Swedish Twin Registry's surveys: (i) "How long did you live in the same home as your twin partner?" and (ii) "How old were you when you moved apart?". These questions were only asked in the SALT survey, meaning that these data are only available for twins born 1886-1958. We consider twins who were separated at age 10 or earlier as reared apart (Finkel et al., 1998). To maintain a sufficient number of observations to analyze, we modify our main measure of investment behavior, *Share in Equities*, to take on zero for individuals who do not participate in the stock market. That is, we do not condition on stock market participation. We also identify all twins in the panel data set, and employ time-series averages over all years that we have data for a given pair of twins. Our final sample of reared apart twins consists of 716 individuals.

Table 8 reports separate model estimates for twins Reared Apart and Reared Together. We find that the A, C, and E components are similar for the two groups. The genetic component, A, is 0.270 (0.280) for twins reared apart (together). It is comforting that the C component is estimated to be zero for twins reared apart as they by definition were not exposed to the same family environment. The shared family component is close to zero, 0.038, also for twins reared together. The non-shared environmental component is 0.730 and 0.682, respectively, for twins who were reared apart versus those who were reared together.

The evidence from twins reared apart provides additional support for our conclusion that there is a significant genetic component that explains cross-sectional heterogeneity in investment and

[34] Note that twins who were reared apart were dropped from the analysis reported so far in the paper.

risk-taking behavior. Even twins who were reared apart, share a substantial component of their investment behavior. That is, individuals are biologically predisposed to certain behaviors in the financial domain.[35]

VI Conclusions

In this paper, we study the foundations of investment and financial risk-taking behavior among individual investors. Our goal was to offer insights into determinants of financial behavior and explain the significant heterogeneity in behavior observed across individuals, differences which have puzzled economists for a long time. Our empirical approach was to decompose the variance in individuals' financial decisions into a genetic component and separate components for the shared and idiosyncratic environments. We examine key investment decisions each individual investor in developed countries faces over the life-cycle, such as stock market participation, asset allocation decisions, and the choice of portfolio risk.

Across these measures of financial behavior, we find that a genetic component accounts for a very substantial proportion of the variation. Specifically, up to 45 percent of the heterogeneity in investment behavior can be explained by a genetic factor. The magnitude of such a genetic factor is very large compared to other individual characteristics such as age, gender, education, and wealth, which have been explored in the existing finance literature. We find that the genetic component explains a significantly larger proportion of the variation across individuals than do an extensive set of individual characteristics combined. Overall, our evidence indicates that an individual's genetic composition is an important determinant of the individual's investment behavior.

Although our evidence shows that nature has a significant impact on an individual's investment behavior, our analysis also demonstrates considerable environmental influences. The most direct

[35]From a statistical identification perspective, we would want separated twins to be adopted by random families. We recognize that a remaining concern with regard to our results is that families who adopt may be a selective, non-random subset, because of screening by adoption authorities. If families who adopt all offer a selective family environment, the identification problem remains. However, we still argue that the approach of studying the investment and financial risk-taking behavior of reared apart twins, with the caveat of non-random adoptee to family matching, is an improvement over analyzing only twins reared together. In addition, the institutional features of Sweden are such that the demand and supply in the market for adoptees are more important than finding matching families that are expected to provide very similar environments for separated twins (or any other adoptees).

evidence supporting this conclusion is that identical twin correlations for the investment behaviors studied are considerably less than one, even though identical twins are genetically identical. Our results indicate that, for the most part, these environmental influences are not shared by individuals growing up in the same family. That is, environmental influences that contribute to individual heterogeneity in financial behavior are those that make family members different. The family environment, i.e., nurture, has an effect on the investment decisions of young individuals, but this effect is not long-lasting (unless frequent contact remains) as it disappears as an individual acquires own experiences relevant for decision-making in the financial domain.

The most important, and perhaps also most surprising, conclusion from our study is that individuals are biologically pre-disposed to certain investment behaviors in the financial domain to such a large extent. This result is not only relevant for our general understanding of the foundations of investor behavior, but it is also of relevance for the effectiveness of public policy intervention related to financial markets. For example, to the extent that behavior among investors is genetic, we would expect that investment behavior can persist despite ample feedback and education. This has implications for the challenges of educating the public (e.g., Lusardi and Mitchell (2007)) on matters relevant for investment decisions.

References

Ameriks, J., Zeldes, S. P., 2004. How do household portfolio shares vary with age? Working Paper, Columbia University, Graduate School of Business.

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.

Ashenfelter, O., Rouse, C., 1998. Income, schooling, and ability: Evidence from a new sample of identical twins. Quarterly Journal of Economics 113 (1), 253–284.

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

Barsky, R. B., Juster, F. T., Kimball, M. S., Shapiro, M. D., 1997. Preference parameters and behavioral heterogeneity: An experimental approach in the health and retirement study. Quarterly Journal of Economics 112, 537–579.

Becker, G. S., 1976. Altruism, egoism, and genetic fitness: Economics and sociobiology. Journal of Economic Literature 14, 817–826.

Becker, G. S., 1991. A note on restaurant pricing and other examples of social influences on price. Journal of Political Economy 99, 1109–1116.

Bikhchandani, S., Hirshleifer, D., Welch, I., 1992. A theory of fads, fashion, custom, and cultural change as informational cascades. Journal of Political Economy 100 (5), 992–1026.

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.

Björklund, A., Lindahl, M., Plug, E., 2006. The origins of intergenerational associations: Lessons from Swedish adoption data. Quarterly Journal of Economics 121, 999–1028.

Bouchard, Jr., 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.

Brown, J. R., Ivković, Z., Smith, P. A., Weisbenner, S., 2008. Neighbors matter: Causal community effects and stock market participation. Journal of Finance 63, 1509–1532.

Brunnermier, M. K., Nagel, S., 2008. Do wealth fluctuations generate time-varying risk aversion? Micro-evidence on individuals' asset allocation. American Economic Review, 713–736.

Calvet, L. E., Campbell, J. Y., Sodini, P., 2007. Down or out: Assessing the welfare costs of household investment mistakes. Journal of Political Economy 115, 707–747.

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

Campbell, J. Y., 2006. Household finance. Journal of Finance 61, 1553–1604.

Cesarini, D., Dawes, C. T., Johannesson, M., Lichtenstein, P., Wallace, B., 2009a. Genetic variation in preferences for giving and risk taking. Quarterly Journal of Economics 124, 809–842.

Cesarini, D., Johannesson, M., Lichtenstein, P., Sandewall, O., Wallace, B., 2009b. Genetic variation in financial decision making. forthcoming Journal of Finance.

Charles, K. K., Hurst, E., 2003. The correlation of wealth across generations. Journal of Political Economy 111, 1155–1182.

Croson, R., Gneezy, U., 2008. Gender differences in preferences. Journal of Economic Literature 47, 1–27.

Curcuru, S. E., Heaton, J., Lucas, D., Moore, D., 2009. Heterogeneity and portfolio choice: Theory and evidence. In: Aït-Sahalia, Y., Hansen, L. P. (Eds.), Handbook of Financial Econometrics. Elsevier Science, North-Holland, Amsterdam, The Netherlands.

Duflo, E., Saez, E., 2002. Participation and investment decisions in a retirement plan: The influence of colleagues' choices. Journal of Public Economics 85 (1), 121–148.

Feng, R., Zhou, G., Zhang, M., Zhang, H., 2009. Analysis of twin data using sas. Biometrics 65, 584–589.

Finkel, D., Pedersen, N. L., Plomin, R., McClearn, G. E., 1998. Longitudinal and cross-sectional twin data on cognitive abilities in adulthood: The Swedish adoption/twin study of aging. Developmental Psychology 34, 1400–1413.

Goldberger, A. S., 1977. Kinometics: Determinants of socioeconomic success within and between families. North-Holland, Amsterdam, The Netherlands, Ch. Twin methods: A skeptical view.

Graham, J. R., Narasimhan, K., 2004. Corporate survival and managerial experiences during the great depression. Working Paper, Duke University, Fuqua School of Business.

Guiso, L., Haliassos, M., Jappelli, T. (Eds.), 2002. Household Portfolios. MIT Press, Cambridge, MA.

Heaton, J., Lucas, D., 2000. Portfolio choice and asset prices: The importance of entrepreneurial risk. Journal of Finance 55, 1163–1198.

Heckman, J. J., 1976. The common structure of statistical models of truncation, sample selection and limited dependent variables and a simple estimator for such models. Annals of Economic and Social Measurement 5, 475–492.

Hirshleifer, J., 1977. Economics from a biological viewpoint. Journal of Law and Economics 20, 1–52.

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

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

Kuhnen, C. M., Chiao, J., 2009. Genetic determinants of financial risk taking. PLoS ONE 4, 1–4.

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

Lang, K. J., Livesley, W. J., Vernon, P. A., 1996. Heritability of the big five personality dimensions and their facets: A twin study. Journal of Personality 63, 577–592.

Levitt, S. D., List, J. A., 2007. What do laboratory experiments measuring social preferences tell us about the real world? Journal of Economic Perspectives 21, 153–174.

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.

Loehlin, J. C., Nichols, R. C., 1976. Heredity, environment, and personality: A study of 850 sets of twins. University of Texas Press, Austin, TX.

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

Madrian, B. C., Shea, D., 2000. Peer effects and savings behavior in employer-sponsored savings plans. University of Chicago, Graduate School of Business, Working Paper.

Malmendier, U., Nagel, S., 2007. Depression Babies: Do Macroeconomic Experiences Affect Risk-Taking? Working Paper, University of California at Berkeley, Department of Economics.

McArdle, J. J., Pescott, C. A., 2005. Mixed effects variance components models for biometric family analysis. Behavior Genetics 35, 631–652.

McClearn, G. E., Johansson, B., Berg, S., Pedersen, N. L., Ahern, F., Petrill, S. A., Plomin, R., 1997. Substantial genetic influence of cognitive abilities in twins 80 or more years old. Science 276, 1560–1563.

Merton, R. C., 1969. Lifetime portfolio selection under uncertainty: The continuous-time case. Review of Economics and Statistic 51, 247–257.

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

Plomin, R., Caspi, A., 1999. Handbook of Personality: Theory and Research. The Guilford Press, New York, NY, Ch. Behavioral Genetics and Personality, pp. 251–276.

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.

Samuelson, P. A., 1969. Lifetime portfolio selection by dynamic stochastic programming. Review of Economics and Statistics 51, 239–246.

Shiller, R. J., 1995. Conversation, information, and herd behavior. American Economic Review 85 (2), 181–185.

Shiller, R. J., Pound, J., 1989. Survey evidence on diffusion of interest and information among investors. Journal of Economic Behavior and Organization 12 (1), 47–66.

Sundén, A. E., Surette, B. J., 1998. Gender differences in the allocation of assets in retirement savings plans. American Economic Review 88, 207–211.

Vissing-Jørgensen, A., 2002a. Limited asset market participation and the elasticity of intertemporal substitution. Journal of Political Economy 110, 825–853.

Vissing-Jørgensen, A., 2002b. Towards an explanation of household portfolio choice heterogeneity: Nonfinancial income and participation cost structures. Working Paper, Northwestern University, Kellogg School of Management.

Table 1
Summary Statistics: Twins

Panel A: Number of Twins by Zygosity and Gender

		Identical Twins			Non-identical Twins				
Birth cohort	Dataset	Male	Female	Total	Same Sex: Male	Same Sex: Female	Opposite Sex	Total	**All Twins**
1886-1958	SALT	2,692	3,752	6,444	4,018	5,326	11,234	20,578	27,022
1959-1986	STAGE	1,810	2,588	4,398	1,250	1,816	3,018	6,084	10,482
Total (*N*)		4,502	6,340	10,842	5,268	7,142	14,252	26,662	37,504
Total (%)		12%	17%	29%	14%	19%	38%	71%	100%

Panel B: Individual Characteristics

	All Twins	**Identical Twins**		**Non-identical Twins**		**Random Sample of Non-Twins**		
Variable	*N*	Mean	Std. Dev.	Mean	Std. Dev.	*N*	Mean	Std. Dev.
Age	37,504	48.69	18.15	54.54	15.81	37,504	52.85	16.74
Education Level 1	33,371	0.17	0.38	0.24	0.43	33,244	0.23	0.42
Education Level 2	33,371	0.45	0.50	0.44	0.50	33,244	0.46	0.50
Education Level 3	33,371	0.37	0.48	0.32	0.47	33,244	0.31	0.46
Disposable Income (USD)	37,504	36,984	39,340	36,113	43,080	37,504	37,267	142,789
Net Worth (USD)	37,504	71,803	176,511	82,615	331,594	37,504	86,967	1,529,036
Business Owner	37,504	0.02	0.14	0.03	0.16	37,504	0.03	0.16
Home Owner	37,504	0.57	0.49	0.61	0.49	37,504	0.59	0.49

Table 1 Panel A reports the number of twins by zygosity (identical vs. non-identical), birth cohort, and gender. Panel B reports cross-sectional means and standard deviations for the sample of all twins as well as for a random sample of age-matched non-twins. *N* provides the number of observations. All data refer to 2002. See Appendix Table A1 for a detailed definition of all variables.

Table 2
Summary Statistics: Portfolio Choices

Panel A: Asset Allocations

	All Twins	**Identical Twins**		**Non-identical Twins**		**Random Sample of Non-Twins**		
Variable	*N*	Mean	Std. Dev.	Mean	Std. Dev.	*N*	Mean	Std. Dev.
Proportion of Financial Assets:								
- in cash	37,504	0.42	0.38	0.43	0.39	37,504	0.44	0.39
- in bonds	37,504	0.04	0.13	0.04	0.14	37,504	0.04	0.14
- in equities (direct)	37,504	0.12	0.24	0.12	0.25	37,504	0.13	0.26
- in equities (funds)	37,504	0.35	0.36	0.33	0.36	37,504	0.31	0.36
- in options	37,504	0.00	0.01	0.00	0.01	37,504	0.00	0.01
- in other	37,504	0.08	0.21	0.08	0.21	37,504	0.08	0.21

Panel B: Measures of Investment and Financial Risk-Taking Behavior

	All Twins	**Identical Twins**		**Non-identical Twins**		**Random Sample of Non-Twins**		
Variable	*N*	Mean	Std. Dev.	Mean	Std. Dev.	*N*	Mean	Std. Dev.
Stock Market Participant	37,504	0.80	0.40	0.78	0.41	37,504	0.76	0.43
Share in Equities	24,396	0.59	0.34	0.57	0.34	22,500	0.58	0.35
Volatility	10,830	0.18	0.10	0.18	0.10	9,102	0.19	0.11

Table 2 Panel A reports cross-sectional means and standard deviations of the amount of financial assets held and the relative investments in different assets for the sample of 37,504 twins as well as for a random sample of 37,504 age-matched non-twins. Panel B reports cross-sectional means and standard deviations of three measures of investment and financial risk taking behavior: Stock Market Participant, a binary indicator of whether an investor holds any equities, Share in Equities, the fraction of financial assets invested in equities conditional on being an equity holder, Volatility, the annualized daily time-series volatility of an investor's equity portfolio. *N* provides the number of observations. All data refer to 2002. See Appendix Table A1 for a detailed definition of all variables.

Table 3
Heritability of Investment and Financial Risk-Taking Behavior

Panel A: Stock Market Participant
(N=37,504)

Model	AIC	Variance Components *A*	*C*	*E*
E	38,968			1.0000
CE	38,378		0.1763	0.8237
			0.0071	0.0071
ACE	**38,262**	**0.2866**	**0.0000**	**0.7134**
		0.0102		**0.0102**

Panel B: Share in Equities
(N=24,396)

Model	AIC	Variance Components *A*	*C*	*E*
E	69,603			1.0000
CE	69,203		0.1799	0.8201
			0.0088	0.0088
ACE	**69,128**	**0.2825**	**0.0000**	**0.7175**
		0.0123		**0.0123**

Panel C: Volatility
(N=10,830)

Model	AIC	Variance Components *A*	*C*	*E*
E	31,017			1.0000
CE	30,702		0.2385	0.7615
			0.0128	0.0128
ACE	**30,638**	**0.3696**	**0.0000**	**0.6304**
		0.0171		**0.0171**

Table 3 reports results from maximum likelihood estimation of linear random effects models. Stock Market Participant (Panel A), Share in Equities (Panel B), and Volatility (Panel C) are modeled as linear functions of *Male, Age, Age - squared* as well as up to three random effects representing additive genetic effects, shared environmental effects, as well as an individual-specific error. In each panel, we report results for a model that only allows for an individual-specific random effect (E model), a model that also allows for a shared environmental effect (CE model), and a model that also allows for an additive genetic effect (ACE model). In each case, we report Akaike's information criterion (AIC), the variance fraction of the combined error term explained by each random effect (*A* – for the additive genetic effects, *C* – for shared environmental effects, *E* – for the individual-specific random effect) as well as the corresponding standard errors. We perform likelihood ratio tests and at the 1% level reject all E models in favor of the corresponding CE models. We also reject all CE models in favor of the corresponding ACE models. We do not report the coefficient estimates for *Male, Age,* and *Age-squared*. *N* provides the number of observations used in each estimation. All data refer to 2002. See Appendix Table A1 for a detailed definition of all variables.

Table 4
Understanding Heterogeneity of Investment and Financial Risk-Taking Behavior

	Stock Market Participant		Share in Equities			Volatility		
	I	II	III	IV	V	VI	VII	VIII
Mean								
Intercept	0.8011	0.9057	0.5840	0.7349	0.6386	0.1815	0.1502	0.1800
	0.0024	0.0229	0.0025	0.0231	0.0237	0.0011	0.0097	0.0147
Male		0.0228		0.0000	0.0187		0.0250	0.0250
		0.0045		0.0047	0.0048		0.0021	0.0021
Age (divided by 100)		-0.4322		-0.2338	-0.6109		0.1749	0.4634
		0.1048		0.1080	0.1098		0.0470	0.1165
Age - squared (divided by 1,000)		0.0408		-0.0095	0.0277		-0.0225	-0.0444
		0.0111		0.0116	0.0118		0.0052	0.0096
Education Level 1		-0.0875		0.0006	-0.0702		-0.0243	-0.0291
		0.0066		0.0070	0.0081		0.0032	0.0036
Education Level 2		-0.0412		0.0051	-0.0282		-0.0106	-0.0142
		0.0051		0.0052	0.0056		0.0024	0.0027
Net Worth (in million SEK)		0.0066		-0.0014	0.0030		0.0022	0.0035
		0.0008		0.0007	0.0007		0.0011	0.0012
Business Owner		0.0142		-0.0584	-0.0461		0.0168	0.0102
		0.0134		0.0136	0.0136		0.0061	0.0065
Home Owner		0.0381		-0.0171	0.0151		0.0017	-0.0043
		0.0048		0.0051	0.0054		0.0024	0.0032
Inverse Mill's Ratio					0.5388			-0.0933
					0.0326			0.0345
Residual Variance	0.1593	0.1571	0.1159	0.1131	0.1117	0.0104	0.0101	0.0101
	0.0013	0.0012	0.0011	0.0011	0.0011	0.0002	0.0001	0.0001
Variance Components								
A	0.2930	0.2925	0.3157	0.2925	0.2932	0.3795	0.3594	0.3585
	0.0108	0.0127	0.0125	0.0127	0.0127	0.0176	0.0179	0.0179
C	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
E	0.7070	0.7075	0.6843	0.7075	0.7068	0.6205	0.6406	0.6415
	0.0108	0.0127	0.0125	0.0127	0.0127	0.0176	0.0179	0.0179
N	33,371	33,371	22,384	22,384	22,384	10,063	10,063	10,063

Table 4 reports results from maximum likelihood estimation of linear random effects models. Stock Market Participant, Share in Equities, and Volatility are modeled as linear functions of observable characteristics as well as three random effects representing additive genetic effects, shared environmental effects as well as an individual-specific error. We report estimates and standard errors for the coefficients associated with the observable characteristics as well as for the variance of the combined error term (*Residual Variance*). We also report estimates and standard errors for the fraction of the residual variance attributable to the additive genetic effects (*A*), the shared environmental effects (*C*) as well as the individual-specific error term (*E*). *N* provides the number of observations used in each estimation. All data refer to 2002. See Appendix Table A1 for a detailed definition of all variables.

Table 5
Robustness

Panel A: Measurement Error

Model	N	A	C	E
			Variance Components	
Stock Market Participant	37,504	0.3531	0.0000	0.6469
		0.0099		0.0099
Share in Equities	24,396	0.3754	0.0000	0.6246
		0.0116		0.0116
Volatility	10,830	0.4454	0.0290	0.5256
		0.0453	0.0342	0.0177

Panel B: Non-Linear Genetic Effects

Model	N	A	D	E
			Variance Components	
Stock Market Participant	37,504	0.2248	0.0754	0.6999
		0.0355	0.0413	0.0124
Share in Equities	24,396	0.2313	0.0609	0.7077
		0.0447	0.0512	0.0146
Volatility	10,830	0.3015	0.0787	0.6197
		0.0663	0.0739	0.0195

Table 5 Panel A reports results from maximum likelihood estimation of linear random effects models. Stock Market Participant, Share in Equities, and Volatility are modeled as linear functions of *Male, Age, Age - squared* as well as three random effects representing additive genetic effects, shared environmental effects as well as an individual-specific error. We report estimates and standard errors for the fraction of the residual variance attributable to the additive genetic effects (*A*), the shared environmental effects (*C*) as well as the individual-specific error term (*E*). All variables are individual-specific time series averages, reflecting all data available between 1998 and 2006, conditional on non-missing data for 2002. Panel B reports results from maximum likelihood estimation of linear mixed effects models. Stock Market Participant, Share in Equities, and Volatility are modeled as linear functions of *Male, Age, Age - squared* as well as three random effects representing additive genetic effects, dominant genetic effects as well as an individual-specific error. We report estimates and standard errors for the fraction of the residual variance attributable to the additive genetic effects (*A*), the dominant genetic effects (*D*) as well as the individual-specific error term (*E*). All data used in Panel B refer to 2002. *N* provides the number of observations used in each estimation. See Appendix Table A1 for a detailed definition of all variables.

Table 6
Differences across Age Groups and Gender

Panel A: Age Groups

		Variance Components		
Model	*N*	*A*	*C*	*E*
Younger than Age 30	3,390	0.4449	0.1973	0.3578
		0.0617	0.0546	0.0188
Age 30 to 54	9,412	0.1921	0.0000	0.8079
		0.0202		0.0202
Age 55 to 79	10,840	0.1725	0.0100	0.8175
		0.0616	0.0406	0.0268
Older than Age 80	754	0.1624	0.0000	0.8376
		0.0752		0.0752

Panel B: Gender

		Variance Components		
Model	*N*	*A*	*C*	*E*
Men	6,812	0.2910	0.0000	0.7090
		0.0205		0.0205
Women	8,602	0.2235	0.0528	0.7237
		0.0564	0.0452	0.0198

Table 6 reports results from maximum likelihood estimation of linear random effects models. Share in Equities is modeled as a linear function of *Male, Age, Age - squared* as well as three random effects representing additive genetic effects, shared environmental effects as well as an individual-specific error. We report estimates and standard errors for the fraction of the residual variance attributable to the additive genetic effects (*A*), the shared environmental effects (*C*) as well as the individual-specific error term (*E*). Panel A presents results for different age groups. Panel B reports results for the subset of male and female twin pairs. *N* provides the number of observations used in each estimation. All data refer to 2002. See Appendix Table A1 for a detailed definition of all variables.

Table 7
Effects of Twin Interaction

Panel A: Summary Statistics

	Identical Twins		**Non-identical Twins**	
Model	*N*	Mean	*N*	Mean
Contacts per Year	9,726	176	24,582	77
Meetings per Year	9,966	93	24,638	37

Panel B: Contact Frequency

		Variance Components		
Model	*N*	*A*	*C*	*E*
Little Contact	5,546	0.1419	0.0000	0.8581
		0.0328		0.0328
Intermediate Contact	10,740	0.1347	0.0563	0.8089
		0.0608	0.0403	0.0264
Lots of Contact	6,404	0.2382	0.1275	0.6343
		0.0617	0.0518	0.0201

Table 7 Panel A reports the cross-sectional mean of the number of contacts and meetings between twins for identical and non-identical twins. Panel B reports results from maximum likelihood estimation of linear random effects models. Share in Equities is modeled as a linear function of *Male, Age, Age - squared* as well as three random effects representing additive genetic effects, shared environmental effects as well as an individual-specific error. We report estimates and standard errors for the fraction of the residual variance attributable to the additive genetic effects (*A*), the shared environmental effects (*C*) as well as the individual-specific error term (*E*), separately for twins with little contact (less than 20 contacts per year), intermediate contact (between 20 and 155 contacts per year), and lots of contact (more than 155 contacts per year). *N* provides the number of observations used in each estimation. Data on twin interaction were collected by the Swedish Twin Registry between 1998 and 2006. All other data refer to 2002. See Appendix Table A1 for a detailed definition of all variables.

Table 8
Evidence from Twins Reared Apart

		Variance Components		
Model	N	A	C	E
Reared apart	716	0.2700	0.0000	0.7300
		0.0906		0.0906
Reared together	32,688	0.2802	0.0383	0.6816
		0.0331	0.0221	0.0143

Table 8 report results from maximum likelihood estimation of linear random effects models. Share in Equities is modeled as a linear function of *Male, Age, Age - squared* as well as three random effects representing additive genetic effects, shared environmental effects as well as an individual-specific error. Differently from above, Share in Equities takes on zero for investors that do not participate in the stock market. We report estimates and standard errors for the fraction of the residual variance attributable to the additive genetic effects (*A*), the shared environmental effects (*C*) as well as the individual-specific error term (*E*), separately for twins reared apart (separated at age 10 or earlier) and reared together. All variables are individual-specific time series averages, reflecting all data available between 1998 and 2006. *N* provides the number of observations used in each estimation. See Appendix Table A1 for a detailed definition of all variables.

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.
Reared apart Twins	A pair of twins that were separated at age ten or earlier. The data are obtained from the Swedish Twin Registry.
Reared together Twins	A pair of twins that were not separated at age ten or earlier. The data are obtained from the Swedish Twin Registry.
Measures of Investment and Financial Risk-Taking Behavior	
Stock Market Participant	An indicator variable that equals one if an individual has non-zero direct or indirect equity investments and zero otherwise.
Share in Equities	The market value of direct and indirect equity investments divided by the market value of all financial assets. This variable is available only for stock market participants and missing for non stock market participants.
Volatility	The annualized daily volatility of an individual's portfolio of direct and indirect equity holdings. We calculate daily equity portfolio returns using portfolio weights reported by Statistics Sweden as of Dec. 31 for a given year as well as daily asset returns during the subsequent year. We then calculate the annualized daily portfolio volatility for every year. The largest one percentile of volatility estimates is set to missing. This variable is only available for those individuals with positive equity investments for which we have complete return data, it is missing otherwise. Asset return data are obtained from a various sources including Datastream, Bloomberg, and Swedish Investment Fund Association.
Sociodemographic Characteristics	
Male	An indicator variable that equals one if an individual is male and zero otherwise. Gender is obtained from the Statistics Sweden.
Age	An individual's age on Dec. 31 of a given year as reported by the Statistics Sweden.
Education Level 1	An indicator variable that equals one if an individual has completed less than nine years of schooling, zero otherwise. Educational information is obtained from Statistics Sweden.
Education Level 2	An indicator variable that equals one if an individual has completed high school but not college, zero otherwise. Educational information is obtained from Statistics Sweden.
Education Level 3	An indicator variable that equals one if an individual has at least completed college, zero otherwise. Educational information is obtained from Statistics Sweden.
Disposable Income	Disposable income of the individual's household as reported by Statistics Sweden in nominal Swedish Krona (SEK) (unless indicated otherwise) for a given year.
Net Worth	The difference between the market value of an individual's assets and her liabilities, calculated by Statistics Sweden at the end of each year and expressed in nominal Swedish Krona (SEK) (unless indicated otherwise).
Financial Assets	The market value of an individual's financial assets as reported by Statistics Sweden at the end of each year, 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.
Business Owner	An indicator variable that equals one if an individual's income from active business activity is more than 50% of the individual's labor income and zero otherwise. The comparison is performed using absolute values of income. Income data are obtained from Statistics Sweden.
Home Owner	An indicator variable that equals one if the market value of owner occupied real estate is positive and zero otherwise. Market values are obtained from Statistics Sweden.
Other	
Contacts per Year	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.
Meetings per Year	The number of meetings 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.

Figure 1
Correlations by Genetic Similarity

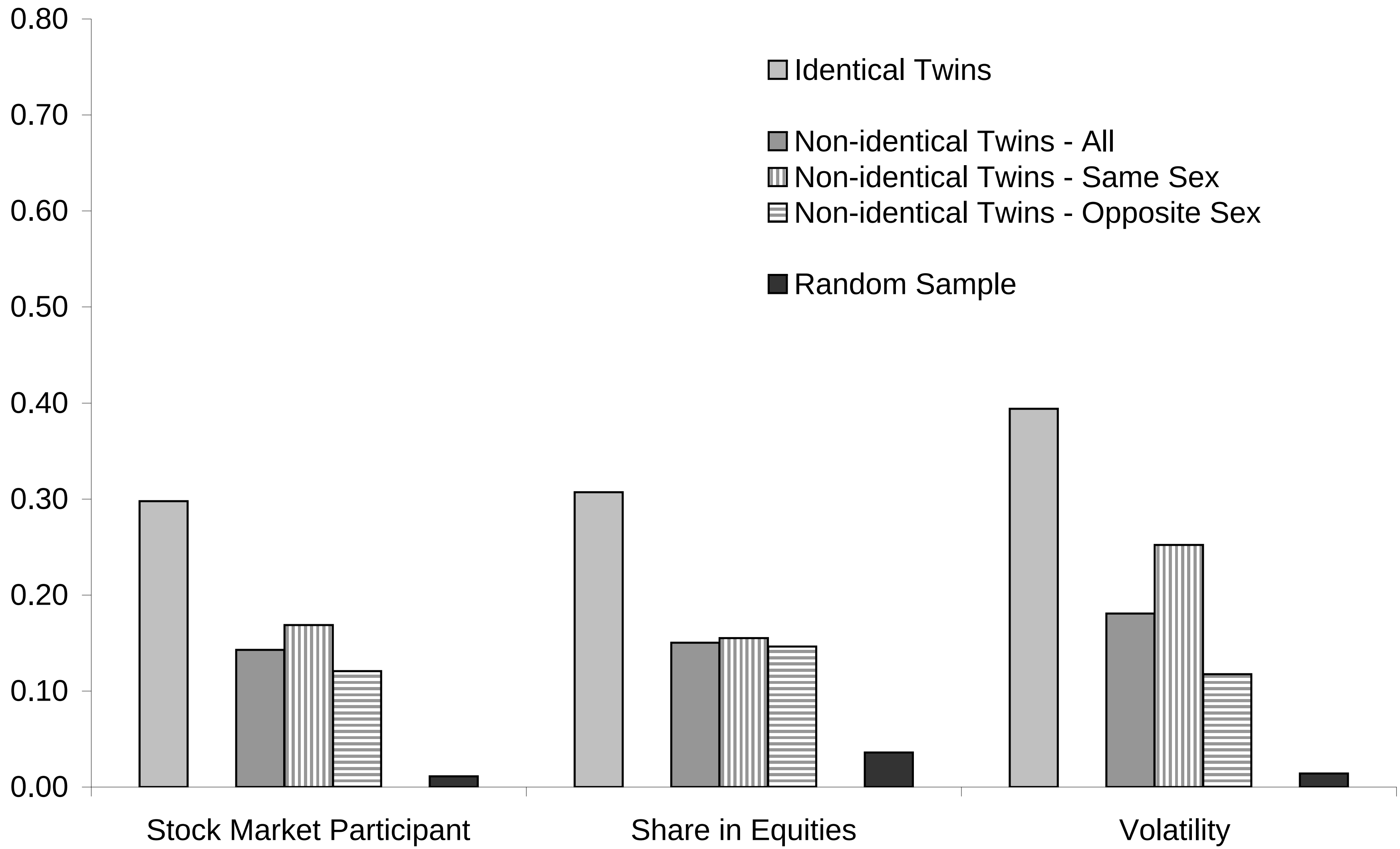

Figure 2:
Share in Equities: Correlations by Age Group

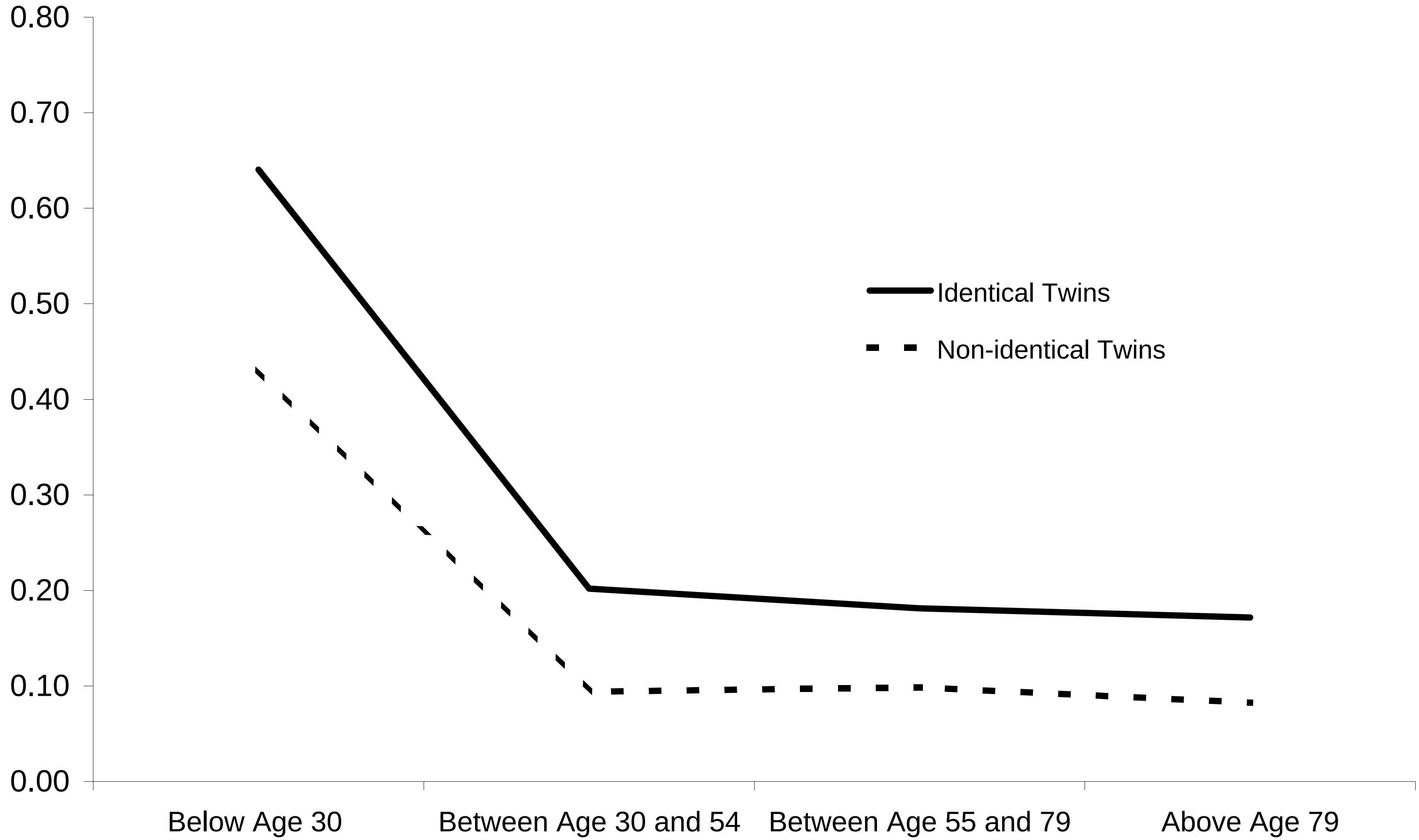

Figure 3:
Share in Equities: Variance Components by Age Group

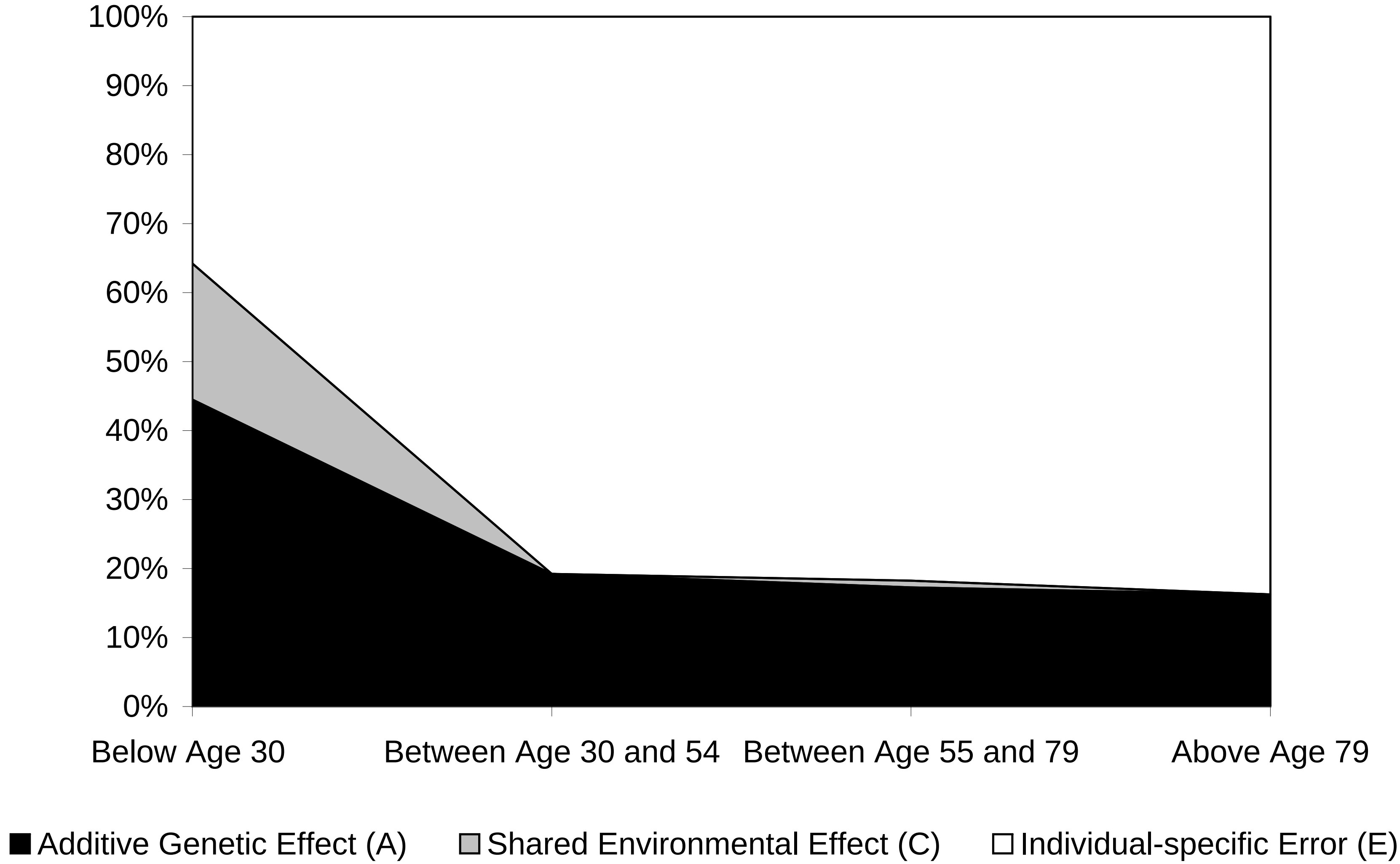

Figure 4:
Share in Equities: Variance Components by Contact Intensity

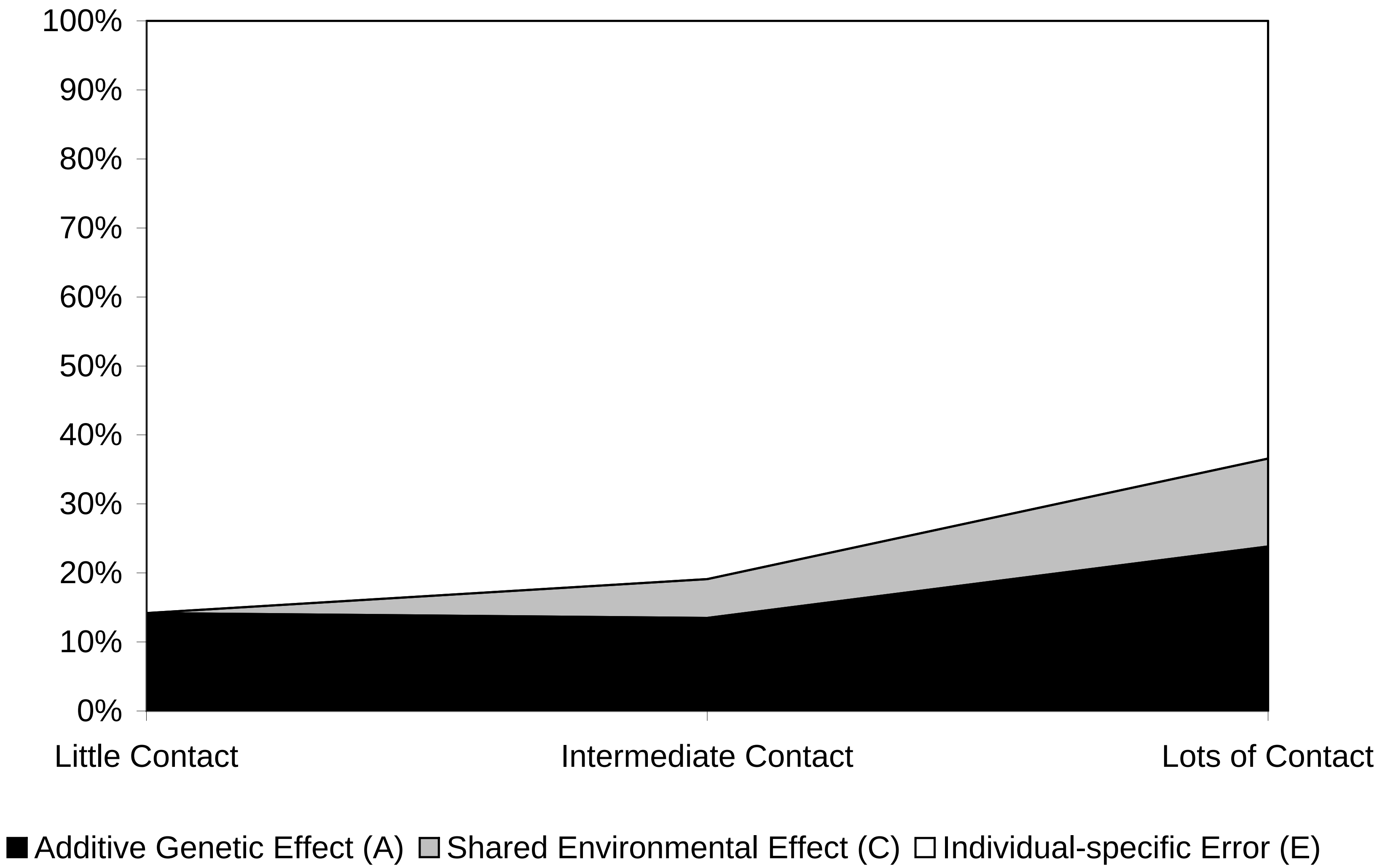

Figure 5:
Share in Equities: Correlation by Contact Intensity