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Talk and Action: What Individual Investors Say and What They Do *

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Abstract. Combining survey responses and trading records of clients of a German retail broker, this paper examines some of the causes for the apparent failure to buy and hold a well-diversified portfolio. The subjective investor attributes gleaned from the survey help explain the variation in actual portfolio and trading choices. Self-reported risk aversion is the single most important determinant of both portfolio diversification and turnover; other things equal, investors who report being more risk tolerant hold less diversified portfolios and trade more aggressively. Less experienced investors similarly tend to churn poorly diversified portfolios. The effect of perceived knowledge on portfolio choice is less clear cut; holding other attributes constant, investors who think themselves knowledgeable about financial securities indeed hold better diversified portfolios, but those who think themselves more knowledgeable than the average investor churn their portfolios more.

1. Introduction

Traditional finance theory recommends that individual investors simply buy and hold the market portfolio, or at least a well-diversified portfolio of stocks. The typical retail investor doesn't; most of those who hold stocks directly hold just a handful of stocks rather than a diversified portfolio (see, e.g., Blume and Friend (1975) and the 1998 U.S. Survey of Consumer Finances (SCF)). Moreover, many retirement plan participants allocate a substantial fraction of their discretionary retirement funds to company stock (see Benartzi (2001), Huberman (2001), and Huberman and Sengmüller (2004)). Analyzing the common stock investments of clients at a US discount brokerage, Goetzmann and Kumar (2002) report that younger and lower-income clients hold less diversified portfolios and suggest a lack of investor sophistication as explanation for poorly diversified portfolios.

The second part of the buy-and-hold suggestion is that individuals do not churn their portfolios which also appears to be rejected in the data. At the end of the 1990s, turnover on the New York Stock Exchange (NYSE) was well above 75% (NYSE (2001)). Although the NYSE is dominated by large institutional investors,

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many of the institutions invest on behalf of individuals; most of the turnover in Nasdaq 100 stocks during 2000 and 2001 can be attributed to individual investors (Griffin et al. (2003)).[1] Using trading records for a sample of U.S. discount brokerage clients, Barber and Odean (2000) report that the frequent traders perform about as well as other investors ignoring trading costs, but do considerably worse when trading costs are taken into account. This is hard to explain with conventional motives for trading such as savings or risk sharing; Odean (1998) suggests overconfidence as an explanation.

This paper is one of the first to confront investors' actual portfolio and trading choices with their stated attitudes toward investing in order to shed light on the apparent failure to buy and hold a well-diversified portfolio. Survey responses, available for a sample of German discount brokerage clients, reveal objective investor attributes such as age, gender, and income as well as subjective attributes such as perceived knowledge, self-reported risk attitude, and the perceived control over investments. The existing empirical literature on investor behavior focuses on objective attributes as proxies for psychological traits – gender as a proxy for overconfidence, for example (see, e.g., Barber and Odean (2001)). This paper departs from the prior literature by using stated perceptions and self-assessments to develop measures for unobservable psychological attributes.

Unobservable psychological attributes, such as risk aversion and overconfidence, are central to the traditional theory of investor behavior as well as to the behavioral approach. Variation in the behavior of investors is often associated with variation in the levels of the attributes across investors, and therefore an empirical examination of these models calls for the elicitation and estimation of these attributes. Such elicitation and estimation is done with questionnaires or experiments in which individuals are asked to answer a series of questions or perform certain tasks. The presumption is that an individual's responses proxy the individual's level of the attribute.

The use of questionnaire- or experiment-based proxies poses two problems. First, in the presence of multiple proposed proxies for the same attribute, it is often the case that individuals' responses are domain-specific and poorly correlated across the proxies. (For measures of risk aversion, see, e.g., the brief review in Weber et al. (2002). For measures of overconfidence, see Glaser and Weber (2004).) This lack of consistency counsels caution in the interpretation of such proxies. The second problem is that studies based on such proxies are difficult to extend to other populations because one would have to estimate those proxies in a new study. Moreover, the proxy may lose its validity for another population.

[1] Contrary to the lack of diversification, however, portfolio churning is concentrated among relatively few individuals; according to survey evidence, nine out of ten retail investors report following a buy-and-hold investment strategy and a similar fraction reports trading less than once a month (ICI and SIA (1999) and the 1998 SCF); Samuelson and Zeckhauser (1988) and Agnew et al. (2003) report little portfolio turnover in retirement accounts.

An alternative to using questionnaire- or experiment-based proxies is to use observables such as gender, age, and location. Their advantage is that they are measured accurately, and can easily be observed for people who were not part of the studied population. The difficulty is in the interpretation of these observables in the context of current models of investor behavior because they do not appear explicitly in the models. Combining information of both types will help in the empirical examination of investor behavior.

In this study, we find that the inclusion of subjective investor attributes offers several insights into investor behavior. Our main result is that the investor's risk attitude, elicited on an ordinal four-point scale similar to that of the US Survey of Consumer Finances, is the most successful variable in explaining cross-sectional variation in both portfolio diversification and turnover. The average annual portfolio volatility among the least risk-averse investors between January 1995 and May 2000 is 45% versus 28% for the most risk-averse investors; on average, portfolios of risk-averse investors contain twice as many positions as those of risk-tolerant investors. The average monthly portfolio turnover of a respondent in the least risk-averse category is more than 30%; by contrast, average turnover in the most risk-averse category is less than 10%. Moreover, including self-reported risk aversion as an explanatory variable in a regression of portfolio turnover on objective investor attributes renders previously documented age and gender effects much less significant (see Barber and Odean (2001)).

The evidence that investor sophistication is associated with better portfolio choices is mixed. Investors who report being wealthier hold better diversified portfolios and churn their portfolios less (see, e.g., Goetzmann and Kumar (2002), Vissing-Jørgensen (2003), and Zhu (2002)). Those who have been investing longer also make better portfolio choices. The effect of perceived knowledge, however, is less clear-cut. Those who perceive themselves as knowledgeable about financial securities indeed hold better diversified portfolios (see Graham et al. (2004)), but those who perceive themselves as better informed about financial securities *than the average investor* churn their portfolios. Such self-professed relative knowledge could be interpreted as a proxy for overconfidence as the sample investors are unlikely to be better informed than the professional investors they are trading with.

Otherwise, support for the hypothesis that overconfidence causes trading – elegantly stated by Odean (1998) – is weak. Survey responses allow us to construct proxies of attributes that have been previously identified as drivers of overconfidence such as an investor's perceived control over his investments or his tendency to attribute gains to his skill and losses to bad luck (see Daniel et al. (1998) and Gervais and Odean (2001)). These measures fail to explain much difference in portfolio diversification and turnover.

Other studies that examine the relation between questionnaire-based proxies for overconfidence and investor behavior in an experiment or actual investor behavior report mixed results. Whereas Biais et al. (2004) and Glaser and Weber (2004) report no relation between an investor's tendency to overestimate the precision of his knowledge and his trading activity, Deaves et al. (2003) do. Glaser and Weber (2004) propose six other proxies for overconfidence and report that none of them helps explain variation in portfolio turnover unless the most aggressive traders are excluded from the analysis.

Although recent papers increasingly rely on surveys to elicit investor attributes (see, e.g., Glaser and Weber (2004), Graham et al. (2004), Guiso et al. (2005), and Vissing-Jørgensen (2003)), the use of surveys raises issues such as inaccurate responses (see, e.g., Campbell (2003)), misunderstood questions (see Bertrand and Mullainathan (2001)), and non-responses biases, in addition to the attribute observability issues mentioned above.

While we cannot independently check the accuracy of, say, self-reported wealth, we find that more than nine out of ten respondents report allocations among twelve different asset classes that sum up to exactly 100%. The self-perception of investors revealed by their survey responses is also fairly accurate. For example, investors who report to be more knowledgeable about financial securities do better on a quiz which tests such knowledge. Investors who report to be more risk tolerant also report holding a considerably greater fraction of their wealth in risky assets such as equities and options as opposed to safe assets such as CDs or money market accounts (see also Kapteyn and Teppa (2002) who report that subjective measures of risk aversion help explain variation in self-reported risk postures).

As only a fraction of those invited to participate in the survey choose to do so, a selection bias might affect our results. To control for this potential bias, we use the investor attributes contained in the brokerage records, which are available for all investors whether they choose to participate in they survey or not, to estimate Heckman two-stage selection models corresponding to our main regressions. The results are little changed.

The remainder of the paper proceeds as follows: Next is a description of the transaction records and the survey data. Section 3 summarizes demographic, socio-economic, and subjective attributes of the survey respondents. Section 4 compares self-reported behavior with actual behavior by relating attributes and attitudes of the sample investors to their actual behavior inferred from the trading records. Section 5 concludes.

2. Data

The analysis in this paper draws on transaction records and questionnaire data obtained for a sample of clients at one of Germany's three largest online brokers. "Online" refers to the broker's ability to process online orders; customers can also place their orders by telephone, fax, or in writing. The broker could be labelled as a "discount" broker because no investment advice is given. Because of their low fees and breadth of their product offering, German online brokers attract a large cross-section of clients ranging from day-traders to retirement savers (during the sample period, the selection of mutual funds offered by online brokers is much greater than that offered by full-service brokers – typically divisions of the large German universal banks that are constrained to sell the products of the banks' asset management divisions). In June 2000, at the end of our sample period, there were almost 1.5 million retail accounts at the five largest German discount brokers (see Van Steenis and Ossig (2000)) – a sizable number, given that the total number of German investors with exposure to individual stocks at the end of 2000 was estimated to be 6.2 million (see Deutsches Aktieninstitut (2003)). Note that all German retail and discount brokerage accounts are taxable accounts as opposed to the US, where tax-deferred accounts, often with a restricted investment menu such as 401(k) accounts, play an important role.

2.1. BROKERAGE RECORDS

The opening position as well as complete transaction records from the account opening date (as early as January 1, 1995) until May 31, 2000 or the account closing date – whichever comes first – are available for all 21,500 prospective participants in the survey, regardless of whether they choose to participate in the survey or not. With these transaction records, client portfolios can be unambiguously reconstructed at a daily frequency. The typical record consists of an identification number, account number, transaction date, buy/sell indicator, type of asset traded, security identification code, number of shares traded, gross transaction value, and transaction fees. In principle, brokerage clients can trade all the bonds, stocks, and options listed on German exchanges, as well as all the mutual funds registered in Germany. Here, the focus is on the investors' individual stock and mutual fund holdings and trades for which Datastream provides comprehensive daily asset price coverage: stocks on Datastream's German research stocks list, dead or delisted stocks on Datastream's dead stocks list for Germany (this includes foreign stocks), and mutual funds registered either in Germany or in Luxembourg. As of May 2000, the lists contain daily prices for 8,213 domestic and foreign stocks and 4,845 mutual funds. These stocks and mutual funds represent over 90% of the clients' holdings and 80% of the trading volume, with the remainder split between bonds, options, and unidentified stocks and mutual funds.[2]

Stocks are classified as domestic or foreign primarily by the first two digits of the stock's International Security Identification Number (ISIN), which identify the country in which the company is registered. This initial classification is manually checked against a data base of company data maintained by WM Datenservice, the organization that officially assigns ISINs to companies registering on German stock exchanges. Mutual funds can be classified into domestic or foreign funds because the broker maintains a list of all the mutual funds offered, classifying them by asset class and geographic focus or investment topic.

[2] The value of the bonds, options, and unidentified stocks and mutual funds held and traded can be estimated from the transaction records.

Upon opening an account, brokerage clients also provide their contact information from which their zip code and gender can be inferred; most account holders also supply their birth date. To calculate the distance between the investor and the German companies in which he holds stock, we collect the zip codes of company headquarters for over 1,200 German companies from WM Datenservice. The zip codes of investors and firms are translated into geographic longitude and latitude by matching them against a list of zip codes and the corresponding geographic coordinates for 6,900 German municipalities.[3]

2.2. SURVEY SAMPLING AND SELECTION

In July 2000, the broker mailed a paper questionnaire to a stratified random sample of 2,300 clients who had opened their account after January 1, 1995, and a random sample of 120 former clients who had closed their account sometime between January 1995 and May 2000. The sample of active clients was stratified based on the number of transactions and the average portfolio size during 1999 – the most recent period for which data were available – to ensure a balanced sample of invited participants that corresponded to the brokerage population. At the same time, an online version of the questionnaire was made available to a random sample of 19,000 clients for whom an email address was on file at the time. The questionnaire elicited information on the investors' investment objectives, risk attitudes and perceptions, investment experience and knowledge, portfolio structure, and demographic and socio-economic status; the time to fill out the questionnaire was estimated to be 20–25 minutes (see Appendix A for details). The goal of the survey – stated on its first page – was to "improve our [the broker's] products to better meet your [the clients'] demands"; brokerage clients who responded to the questionnaire could enroll in a raffle to win Deutsche Mark (DEM) 6,000 (about 3,500 US dollars (USD) at the average DEM/USD rate of 1.73 during the sample period) or a weekend for two in New York City. By the end of August 2000, the firm had collected 577 responses to the paper survey and 768 responses to the online survey.

Table I contrasts account and investor characteristics of respondents and non-respondents. Average account statistics across the two groups are quite similar. Portfolios are worth around DEM 130,000, on average, slightly less than half of the portfolio is invested in domestic stocks either held directly or through mutual funds, the ratio of the distance between account holder and account assets to distance between account holder and the market portfolio of stocks is 92% (meaning that the investor's actual portfolio is 8% closer to his home than the market portfolio of German stocks (see Coval and Moskowitz (1999))), average prior monthly returns are 2%, and portfolio volatility, measured as the annualized standard deviation of daily portfolio returns, is 35%. In particular, respondents and non-respondents exhibit similar trading intensities; average monthly portfolio turnover – measured as average monthly purchases and sales divided by twice the

[3] This list can be downloaded from http://www.astrologix.de/download/, last viewed 3/26/02.

Table I. Characteristics of survey respondents and non-respondents

Portfolio characteristics are calculated from the complete daily transaction history available for each client – whether he chooses or refuses to respond – from the day when the account was opened until May 31, 2000 or the day when the account was closed, whichever comes first. Average monthly turnover is defined as the absolute sum of purchases and sales of stocks and mutual funds divided by the number of months the account has been active times the average portfolio value of stocks and mutual funds (portfolio values are calculated at the end of every month the account has been open). To estimate portfolio volatility, we assume that the clients will hold their month-end positions for one month and calculate a value-weighted portfolio return for the following month; the average monthly portfolio return is the geometric average of these monthly returns. Annualized portfolio volatility is the standard deviation of the logarithm of monthly returns multiplied by $\sqrt{12}$. The Herfindahl-Hirschmann Index, value, home bias, and local bias of the portfolio are calculated as of 5/31/2000 (or as averages across active account months for clients who close their accounts before 5/31/2000) – see also Figure 1 for a definition of the portfolio attributes. Portfolio value is reported in Deutsche Mark [DEM]; during the sample period, one US Dollar [USD] corresponds to roughly DEM 1.7. "Fraction of domestic assets" refers to the DEM value of German stocks and mutual funds investing in German assets as a fraction of the DEM value of all stocks and mutual funds held by the client. The local bias of a portfolio is defined as one minus the ratio of the distance between the investor and his portfolio divided by the distance between the investor and the market portfolio. All investor characteristics are gleaned from information recorded by the broker upon account opening (and account closing). The gender of the account holder is inferred from the salutation which is part of the address to which account information is sent (e.g., if the account is jointly owned by a couple but the account correspondence is addressed to the female partner, the account holder would be identified as female). Age is supplied voluntarily upon account opening. The "distance to broker" is calculated based on the distance between the zip codes of investor and broker; the distance is missing if the account holder lives outside of Germany. If there is a statistically significant difference between attribute means, proportions, or medians reported for the two samples, it is noted by asterisks in the mean and median columns of the non-respondent sample. The mean comparison tests allow for different variances within the two groups; ***/**/* indicate that the means, proportions, or medians are significantly different at the 1%/5%/10% level.

Number of observations		1,345 Respondents				20,183 Non-respondents			
Portfolio characteristics	Units	Nobs	Mean	Std	Median	Nobs	Mean	Std	Median
Average monthly portfolio turnover		1,343	17%	34%	9%	20,093	16%	63%	8%
Annualized portfolio volatility		1,341	35%	17%	30%	20,063	35%	18%	30%
Monthly portfolio return		1,342	2.0%	2.6%	1.8%	20,110	1.9%	3.9%	1.7%
Herfindahl-Hirschmann Index		1,343	20%	24%	11%	20,113	25%***	29%	14%
Portfolio value	DEM '000s	1,345	130	237	55	20,183	134	372	47
Fraction of domestic assets		1,343	46%	33%	44%	20,113	46%	35%	42%
Local bias of portfolio		1,271	8.0%	32.3%	4.9%	18,672	7.7%	34.1%	4.3%

Table I. Characteristics of survey respondents and non-respondents (continued)

Number of observations		1,345 Respondents				20,183 Non-respondents			
Investor characteristics	Units	Nobs	Mean	Std	Median	Nobs	Mean	Std	Median
Fraction male		1,342	88%			19,708	83%***		
Age of accountholder	years	1,022	38.9	11.1	36.3	15,508	39.7**	12.9	37.5
Account tenure	years	1,345	3.3	1.3	2.9	20,183	3.2**	1.3	2.9
Fraction of former customers		1,345	1%			20,183	1%		
Distance to broker	km	1,313	303	190	314	19,676	311	192	305

Variable	Description
HHI	End-of-period Herfindahl-Hirschmann Index value for a given account. (The HHI is defined as the sum of the squared portfolio weights. For the purpose of the HHI calculations, mutual funds are assumed to consist of 100 equally-weighted, non-overlapping, positions.)
Home bias	Fraction of the investor's equity portfolio invested in German stocks and mutual funds investing in German stocks.
Local bias	Distance measure as calculated by Coval and Moskowitz (1999): 1 - distance of account holdings from customer/ distance of market portfolio from investor. A local bias of 0.05 means that the customer holds a portfolio that is 5% closer to him than the market portfolio. Mutual funds are assumed to have the same distance from the investor as the market portfolio.
Portfolio size	DEM value of all stocks, stock certificates, and mutual funds held by an investor on May 31, 2000
Gross/net portfolio return	Average monthly return adjusted for dividends and transactions. Gross return is before commissions, net return is after commissions.
Portfolio turnover	One plus the sum of the absolute DEM value of transactions in stocks, stock certificates, and mutual funds during a period, divided by the twice the average portfolio value during that period.
Portfolio volatility	Annualized standard deviation of portfolio returns during a given period.

Figure 1. Definition of variables constructed from brokerage records.

average portfolio value (all averages are calculated between account opening and May 31, 2000 or account closing, whichever comes first) – is 17% for respondents and 16% for non-respondents. The one difference is that survey respondents hold less concentrated portfolios. The average Herfindahl-Hirschmann Index (HHI), the sum of squared portfolio weights, of a respondent's portfolio is 20%, which corresponds to an equally weighted portfolio of five stocks; the average HHI of a non-respondent's portfolio is 25%, which corresponds to an equally weighted portfolio of four stocks. Respondents are more predominantly male, ten months younger, and have been clients for about one month longer, on average.

3. Self-Reported Investor Attributes

This section summarizes the sample of survey respondents along different characteristics that will be used to explain cross-sectional variation in actual investor behavior. The characterization allows us to contrast the sample with the greater population of German households and household investors. Moreover, we assess the quality and internal consistency of self-reported attitudes.

3.1. OBJECTIVE ATTRIBUTES

The sample of brokerage clients differs substantially from the broader population of German households along demographic and socio-economic dimensions. Table II provides the details. Almost nine out of ten respondents are male, far exceeding

Variable	Description
Actual knowledge (quiz)	Respondents' score in a knowledge quiz consisting of 7 true/false questions on investment and trading concepts. For every (in-) correct answer, a point is added (subtracted). See Section 3 for details of the construction.
Actual knowledge (risk)	Dummy variable: one if respondent correctly ranks different assets according to their riskiness and zero otherwise. See Section 3 for details of the construction.
Age	Age of respondent in years.
College	Dummy variable: one if respondent has a college education and zero otherwise.
Experience	Length of experience in the stock market in years.
Gender	Dummy variable: one if respondent is male and zero if female.
Illusion of control	Score constructed from perceived control over the outcome of risky propositions. See Section 3 for details of the construction.
Income	Gross annual income in DEM.
Perceived knowledge	Score constructed from self-assessed knowledge about different asset classes such as stocks, bonds, options, or mutual funds. See Section 3 for details of the construction.
Relative knowledge	Investor agreement with statement "I am much better informed about financial securities than the typical investor", ranging from 1 (strongly disagree) to 4 (strongly agree).
Risk aversion	Investor agreement with "high expected returns, high risk"- investment profile, expressed in categories ranging from 1 (strongly disagree) to 4 (strongly agree). See Section 3 for details of the construction.
Riskfrac	Fraction of wealth invested in non-fixed income financial securities (i.e., the sum of allocations to stocks, mutual funds, and options divided by self-reported wealth including real estate).
Self-attribution bias	Score constructed from self-reported attitude towards attribution of investment gains and losses. See Section 3 for details of the construction.
Self-employed	Dummy variable: one if respondent is self-employed and zero otherwise.
Wealth	Total wealth in DEM.

Figure 2. Definition of variables constructed from survey responses.

the 69% fraction of male-headed households in the German household population. The median respondent age is 38, with most brokerage customers in their early thirties to mid forties; thirteen years younger than the typical German household head. The level of self-reported educational achievement of the brokerage clients is impressive; more than two thirds of the sample have attended college, while the population average is a mere 15%. These findings can be, at least partly, explained by self-selection; an online broker will appeal more to those comfortable with computers and the internet – a younger, well-educated, and predominantly male crowd. The self-employed are also over-represented in the investor sample; unlike employees, the self-employed do not have to save for retirement within the state pension system and are thus more interested in holding retirement assets in

Table II. Attributes of respondents, German investors, and German households

Survey participant statistics, reported in Column (1), are computed from the responses to the survey. Attributes of German households or rather household heads (hh heads), reported in Column (2), are supplied through the German Statistics Bureau (see Statistisches Bundesamt (1999) and Börsch-Supan and Eymann (2000)). Income refers to household, not household head, income. Column (3) contains attributes of Germans who own stocks or mutual funds and participate in a survey commissioned by the Deutsches Aktieninstitut (2000). This survey treats a couple who jointly owns stock as one male and one female investor.

		(1)	(2)	(3)
Unit of observation		Respondent	Hh head	Investor
Number of units		1,345	37,800,000	8,100,000
Gender	[% male]	88%	69%	60%
Age	[years]			
	Lower Quartile	32	37	34
	Median	38	51	45
	Upper Quartile	48	65	57
College education	[%]	70%	15%	41%
Self-employed	[%]	17%	7%	9%
Gross income	[DEM ’000s]			
	Lower Quartile	63	35	59
	Median	88	56	78
	Upper Quartile	125	83	108
Wealth	[DEM ’000s]			
	Lower Quartile	80	25	n/a
	Median	325	120	n/a
	Upper Quartile	750	325	n/a

brokerage accounts, other things equal. Finally, survey respondents report a median gross annual income of DEM 88,000, significantly greater than the estimated median gross income of DEM 56,000 for a typical West German household (see Münnich (2001)) and DEM 78,000 for a typical West German investor (based on a survey of West Germans who hold stocks either directly or through mutual funds (see Deutsches Aktieninstitut (2000))). According to the German Statistics Bureau (Münnich (2001)), less than 20% of West German households had an annual gross income exceeding DEM 88,000 during the sample period.

The differences between the greater population of German equity investors and German households are similar to the differences between the survey respondents and German households documented above: equity investors are typically younger, better educated, more likely to be self-employed, and earn higher incomes than household heads without exposure to the stock market. Especially the differences in education and income between stock market participants and non-participants are consistent with Haliassos and Bertaut (1995) and Vissing-Jørgensen (2002) who report that informational barriers as well as lower and more volatile non-financial income help explain limited stock market participation.

In addition to gross income, the survey respondents report their wealth as well as their overall asset allocation across financial and real estate categories (see Appendix E). The internal consistency of the answers is remarkable; although there are twelve asset categories and the allocation question is towards the end of a lengthy questionnaire, nine out of ten respondents report allocations that sum to exactly 100% (on average, respondents report allocations to four asset classes). About one third of the respondents' combined wealth is in real estate, 30% in individual stocks, and 15% in stock funds. The remaining fifth is split between life insurance, bonds, and short- to medium-term savings. In contrast, German households held over half of their combined net financial and real estate wealth in real estate and less than 10% in individual stocks and mutual funds at the end of 1997, according to statistics compiled by the Deutsche Bundesbank (1999) (see also Börsch-Supan and Eymann (2000)).

3.2. SUBJECTIVE ATTRIBUTES

In addition to objective attributes such as gender or income, the survey elicits attributes that require the respondents to make an assessment, e.g., regarding their knowledge about financial assets or their preferences for investments featuring high risk and high expected returns. On the one hand, using answers to subjective questions raises obvious concerns, e.g., that people might give inaccurate answers or that they might "not mean what they say" (see, e.g., Bertrand and Mullainathan (2001)). On the other hand, subjective questions could be appealing because they are relatively easy to understand. Kapteyn and Teppa (2002) report that measures of risk aversion based on answers to subjective questions are better at explaining investor behavior – specifically, the cross-sectional variation in the fraction of wealth invested in risky assets – than measures of risk aversion based on the respondents' choices in gambles over lifetime income (the method used by Barsky et al. (1997)).

3.2.1. *Investment experience and knowledge*

Survey responses allow us to construct measures of investment experience and knowledge. In addition to objective attributes – education, income, and wealth, for example – self-assessments of experience and knowledge about financial assets can be proxies for investor sophistication. In turn, measures for sophistication can be related to actual investor behavior such as trading activity to address whether more sophisticated investors churn their portfolios less, for example.

Investors report the length of their financial experience (see Appendix B), on average seven and a half years. They also assess their knowledge of eleven categories of financial instruments in terms of how well they could explain the instruments to an imaginary friend (see Appendix B) on a scale of 1 (don't know/cannot explain) to 4 (know/can explain very well). The sum of the knowledge scores across the different assets, ranging from 11 to 44, is a measure of perceived knowledge. Most respondents claim to be able to explain all the financial asset categories either well or very well: the median respondent scores a 38 out of 44; this score will be referred to as perceived knowledge. The respondents also assess their knowledge of financial securities relative to that of the average investor by reporting their agreement with "I am significantly better informed about financial securities than the average investor" on a scale of 1 (strongly disagree) to 4 (strongly agree); we use the scale to construct a relative knowledge variable. Almost nine out of ten respondents either agree or strongly agree with the notion of being better informed than the average investor.

Panels A–C of Table III report characteristics of investors grouped by self-reported experience, perceived knowledge, and relative knowledge across asset classes. Those with longer stock market experience and those who perceive themselves as more knowledgeable – in absolute terms or relative to other investors – are more predominantly male, better educated, wealthier, and earn higher incomes. Investor age is strongly positively correlated with the length of experience, only weakly correlated with perceived knowledge, and uncorrelated with relative knowledge.

In addition to measures of perceived knowledge, the survey offers two natural proxies for actual knowledge. *After* assessing their knowledge about financial securities, the survey participants are given a short quiz (see Appendix C), consisting of seven true/false questions. The quiz score is calculated as follows: for each correct answer, one point is added to the score, and for each incorrect answer, one point is subtracted. The questions test knowledge of investing terms and concepts, e.g., whether investors know the tax implications of short-term investments, the definition of a price earnings ratio, or that of a stop-loss order. On average, respondents get four out of the seven questions right. Panel D of Table III shows that those who perceive themselves as more knowledgeable – male, better educated, and higher-income respondents – also do better on the quiz.

Another measure of actual knowledge can be derived from the respondents' risk evaluations of different asset classes. Survey participants rank the riskiness of different asset categories on a scale from 1 (safe) to 10 (extremely risky) (see Appendix D). We assign a dummy variable that takes a value of one if the respondents' ranking of asset categories satisfies the following inequalities: bonds are at least as risky ($\geq$) as savings accounts, bonds $\geq$ bond funds, stocks $>$ bonds, stocks $\geq$ stock funds, stocks $\geq$ index certificates, options $>$ stocks. Three out of five respondents – in particular younger and better educated respondents – make risk assessments in line with the above inequalities. These respondents also do significantly better on the quiz; on average, they get one more question right.

Table III. Demographic and socio-economic attributes of investors grouped by sophistication

Panels A through D characterize investors grouped by different self-reported measures of sophistication: (A) length of stock-market experience (reported in years), (B) self-assessed knowledge (a score between 11 and 44), (C) perceived knowledge relative to the average investor (expressed on an ordinal four-point scale ranging from "much less informed" to "much better informed" – we combine the categories of the relatively "much less informed" and "less informed" as only seven respondents consider themselves much less informed than the average investor), (D) actual knowledge measured by the investor's performance in a short quiz (a score ranging between zero and seven), and (E) actual knowledge measured by their ranking different asset classes according to risk (a dummy variable that is one if respondents correctly rank the relative riskiness of the asset classes). See Figures 1 and 2 for a definition of the attributes and their sources. In Panels A, B, and D, the categories are formed by sorting investors along the corresponding attribute into approximately equally sized groups. Due to clustering of the attributes at certain values, the fraction of households in a "quartile" may deviate from 25%. Note: ***/**/* indicate that the means or proportions of the top and bottom groups are significantly different at the 1%/5%/10% level, allowing for unequal variances when testing for differences in means.

	(1) Fraction of respondents	(2) Gender of respondent [% male]	(3) Mean age [years]	(4) College degree [%]	(5) Self-employed [%]	(6) Income Mean [DEM '000s]	(7) Wealth Mean [DEM '000s]
Panel A: Length of experience							
1 (shortest)	10%	84%	35	64%	14%	74	168
2	28%	85%	38	70%	16%	86	268
3	32%	89%	40	68%	17%	90	358
4 (longest)	30%	94%***	46***	72%*	19%	110***	561***
Panel B: Perceived knowledge							
1 (low)	26%	82%	39	63%	14%	80	262
2	26%	90%	41	67%	15%	94	362
3	24%	92%	41	74%	16%	97	388
4 (high)	24%	91%***	41**	75%***	23%***	103***	489***

Table III. Demographic and socio-economic attributes of investors grouped by sophistication (continued)

	(1) Fraction of respondents	(2) Gender of respondent [% male]	(3) Mean age [years]	(4) College degree [%]	(5) Self-employed [%]	(6) Income Mean [DEM '000s]	(7) Wealth Mean [DEM '000s]
Panel C: Relative knowledge							
1 and 2 (low)	10%	78%	41	69%	12%	82	273
3	47%	90%	41	69%	15%	93	359
4 (high)	43%	91%***	41	70%	21%**	97***	444***
Panel D: Actual knowledge (quiz score)							
1 (low)	31%	85%	41	61%	17%	83	316
2	40%	89%	41	72%	17%	97	380
3	44%	91%	41	70%	14%	96	390
4 (high)	15%	93%***	40	79%***	21%	95**	414***
Panel E: Actual knowledge (risk assessment)							
0 (wrong)	39%	87%	43	64%	17%	91	356
1 (right)	61%	91%**	40***	73%***	17%	95	383

Do those who report knowing more actually know more? Table IV reports the results of OLS and ordered probit regressions of perceived knowledge and relative knowledge on demographic and socio-economic investor attributes as well as measures of actual knowledge. Perceived knowledge, with its 34 different categories, is treated as a continuous variable and the regressions are estimated using OLS. The relative knowledge regressions are estimated using ordered probit, as there are only four relative knowledge categories. However, the sign and statistical significance of the coefficients in both regressions are insensitive to the specification chosen. The results of the regression of perceived knowledge on demographic and socio-economic investor attributes, reported in Column (1) of Table IV, reveals two differences relative to the univariate correlations reported in Table III; the explanatory power of the wealth variable swamps that of the income variable in all regressions and investor age is *negatively* related to perceived knowledge, other things equal. Column (2) of Table IV shows that perceived knowledge is strongly positively related to measures of experience and actual knowledge – those who report to know more actually know more. Combining the explanatory variables from the two previous regressions yields similar results (see Column (4) of Table IV). The remaining columns of Table IV report similar regressions, but with relative knowledge as the dependent variable. Column (4) and (5) of Table IV show that all but one of the investor attributes that explain differences in perceived knowledge also explain differences in relative knowledge; college-educated investors consider themselves more knowledgeable than those without a college education, but do not assert to know more than the average investor, other things equal. Column (6) reports the results of a regression with investor attributes and objective measures of knowledge as explanatory variables. Including measures of actual knowledge renders the gender coefficient insignificant which suggests that male investors' belief in their greater relative knowledge is based on fact rather than hubris. Finally, Column (7) shows that differences in perceived knowledge can explain substantial variation in relative knowledge, holding other investor attributes constant.

3.2.2. *Drivers of Overconfidence*

Recent theoretical work, e.g., by Benos (1998) and Odean (1998), proposes that overconfidence causes trading. Overconfident investors trade more readily on signals about differences between current and future prices of an asset because they overestimate the precision of their signals relative to the precision of other traders' signals or, more generally, they overestimate their trading skills. Analyzing a sample of US discount brokerage clients who switch from phone-based to online trading, Barber and Odean (2002) "posit that online investors become more overconfident once online for three reasons: the self-attribution bias, an illusion of knowledge, and an illusion of control." (see also Daniel et al. (1998) and Gervais and Odean (2001)). Overconfidence is an appealing theoretical concept. Empirically, however, it is challenging to produce an observable which correlates with individuals' overconfidence.

Table IV. Perceived and relative knowledge versus displayed knowledge

The dependent variable in Columns (1)–(3) is a score of perceived knowledge constructed from respondents assessing their knowledge about financial securities (see Appendix B). Columns (1)–(3) report OLS estimates from regressions of the perceived knowledge score on various investor attributes. Columns (4)–(7) report ordered probit estimates from regressions of relative knowledge on different sets of investor attributes. See Figures 1 and 2 for a definition of the attributes and their sources. *ln* denotes the natural logarithm. Standard errors are in parentheses. The standard errors in Columns (1)–(3) are corrected for heteroskedasticity as suggested by White (1980). Note: ***/**/* indicate that the coefficient estimates are significantly different from zero at the 1%/5%/10% level.

Dependent variable	(1) Perceived knowledge	(2) Perceived knowledge	(3) Perceived knowledge	(4) Relative knowledge	(5) Relative knowledge	(6) Relative knowledge	(7) Relative knowledge
Constant	29.448***	28.276***	25.318***				
	(1.339)	(0.681)	(1.362)				
Gender	2.206***		1.397**	0.274**		0.114	0.029
	(0.589)		(0.543)	(0.120)		(0.123)	(0.125)
Age	−0.043***		−0.043***	−0.012***		−0.015***	−0.013***
	(0.015)		(0.014)	(0.004)		(0.004)	(0.004)
College education	1.369***		1.042***	−0.025		−0.089	−0.161**
	(0.359)		(0.332)	(0.078)		(0.080)	(0.081)
Self-employed	0.278		0.459	0.207**		0.262***	0.244**
	(0.415)		(0.387)	(0.097)		(0.099)	(0.100)

Table IV. Perceived and relative knowledge versus displayed knowledge (continued)

Dependent variable	(1) Perceived knowledge	(2) Perceived knowledge	(3) Perceived knowledge	(4) Relative knowledge	(5) Relative knowledge	(6) Relative knowledge	(7) Relative knowledge
ln(Income)	0.153		0.112	0.013		0.001	−0.003
	(0.303)		(0.284)	(0.067)		(0.068)	(0.069)
ln(Wealth)	1.145***		0.625***	0.201***		0.098***	0.061
	(0.158)		(0.150)	(0.035)		(0.037)	(0.038)
Experience		0.327***	0.275***		0.071***	0.071***	0.056***
		(0.032)	(0.034)		(0.009)	(0.010)	(0.010)
Actual knowledge		1.178***	1.065***		0.245***	0.239***	0.182***
(quiz)		(0.117)	(0.118)		(0.029)	(0.030)	(0.031)
Actual knowledge		0.764**	0.452		0.011	−0.034	−0.064
(risk assessment)		(0.296)	(0.293)		(0.074)	(0.076)	(0.077)
Perceived knowledge							0.062***
							(0.008)
Ancillary statistics							
Number of observations	1068	1068	1068	1068	1068	1068	1068
(Pseudo) R^2	10.8%	19.5%	23.2%	2.6%	7.7%	9.0%	11.9%

Survey responses allow us to construct direct measures of drivers of overconfidence and therefore conduct tighter tests of the overconfidence hypothesis than possible in the earlier literature (e.g., Barber and Odean (2001) and Barber and Odean (2002)). The self-enhancing attribution bias refers to the tendency to overly attribute successes to one's skill (the psychological evidence for a self-protective attribution bias, i.e., the tendency to blame external factors for failure, is more mixed (see, e.g., the survey of Miller and Ross (1975))). To estimate the self-enhancing attribution bias, we consider the extent to which survey participants agree – on a four-point scale from 1 (totally disagree) to 4 (fully agree)– with the following statement: "My past investment successes were, above all, due to my specific skills." Investors are also asked to indicate their agreement with the statement "My instinct has often helped me to make financially successful investments." The responses to the two statements are significantly positively correlated and the results reported below are robust to the choice of the bias measure. It is also noteworthy that the two proxies for drivers of overconfidence are positively correlated; the correlation coefficient between the proxy for self-attribution bias and the proxy for illusion of control is 0.25 and significant at the 1% level. Column (1) of Table V reports the results of an ordered probit regression of this proxy for the self-enhancing attribution bias on the demographic and socio-economic variables. Male and wealthier investors are more prone to taking responsibility for their investment successes, other things equal. Interestingly, the gender and wealth coefficients are rendered insignificant when we include the investment experience and knowledge variables (see Column (2) of Table V.) Relative knowledge, in particular, is strongly positively correlated with the tendency to attribute success to skill.

"Illusion of control" usually refers to a decision maker's erroneous expectation to be able to affect chance outcomes or to do better than what would be warranted by objective probabilities (see Langer (1975)). Survey participants indicate their agreement – on a four-point scale from 1 (strongly disagree) to 4 (strongly agree) – with four statements designed to elicit perceived control of the decision maker in risky situations: 1. "When I make plans, I am certain that they will work out," 2. "I always know the status of my personal finances," 3. "I am in control of my personal finances," and 4. "I control and am fully responsible for the results of my investment decisions." Cronbach's alpha for the control score – the average of the individual scores – is 76%, indicating that the four survey items reliably elicit a single underlying construct.[4] Presumably, individuals with higher control scores are more likely to suffer from an illusion of control. The results of an ordered probit regression of the control score on the demographic and socio-economic variables, reported in Column (3) of Table V, show that younger and wealthier investors feel more strongly in control of their finances and investments, other things equal.

[4] Cronbach's measure is defined as $\alpha \equiv \frac{N}{N-1}\left[1 - \frac{\sum_{j=1}^{N}\sigma_j^2}{\sum_{j=1}^{N}\sum_{k=1}^{N}\sigma_{jk}}\right]$, where N is the number of individual scores (here three), σ_j^2 is the variance of individual score j, and σ_{jk} is the covariance of the scores j and k (see Cronbach (1951)).

Table V. The relation between proxies for overconfidence and other investor attributes

This table report the estimates from ordered probit regressions of proxies for overconfidence on objective and subjective investor attributes. The dependent variable in Columns (1) and (2) is the extent to which respondents take responsibility for their investment successes, measured on an ordinal four-point scale, which serves as a proxy for the self-enhancing attribution bias. The dependent variable in Columns (3) and (4) is the extent to which respondents feel "in control" of their investments which serves as a proxy for "illusion of control". See Figures 1 and 2 for a definition of the attributes and their sources. *ln* denotes the natural logarithm. Standard errors are in parentheses. Note: ***/**/* indicate that the coefficient estimates are significantly different from zero at the 1%/5%/10% level.

Dependent variable:	(1)	(2)	(3)	(4)
	Self-enhancing attribution bias		Illusion of control	
Gender	0.264**	0.198	0.180	0.078
	(0.123)	(0.127)	(0.123)	(0.126)
Age	0.000	0.004	−0.012***	−0.008**
	(0.004)	(0.004)	(0.004)	(0.004)
College education	−0.121	−0.128	0.020	−0.010
	(0.079)	(0.082)	(0.079)	(0.081)
Self-employed	−0.063	−0.123	−0.091	−0.144
	(0.095)	(0.097)	(0.094)	(0.095)
ln(Income)	0.017	0.007	−0.073	−0.082
	(0.067)	(0.068)	(0.067)	(0.068)
ln(Wealth)	0.089**	0.020	0.125***	0.049
	(0.035)	(0.038)	(0.035)	(0.038)
Experience		0.003		−0.005
		(0.010)		(0.010)
Actual knowledge		−0.007		0.049
(quiz)		(0.032)		(0.031)
Actual knowledge		0.010		0.040
(risk assessment)		(0.077)		(0.075)
Perceived knowledge		−0.003		0.012
		(0.008)		(0.008)
Relative knowledge		0.613***		0.503***
		(0.064)		(0.061)
Ancillary statistics				
Number of observations	974	974	974	974
Pseudo R^2	0.8%	6.3%	0.6%	4.0%

However, when relative knowledge is included as an explanatory variable, objective investor attributes lose their explanatory power (see Column (4) of Table V).

The strong correlation between relative knowledge and the proxies for overconfidence is noteworthy. One interpretation is that relative knowledge itself is a more direct driver of overconfidence. The overwhelming tendency of the respondents to think themselves better informed than the average investor is reminiscent of Svenson (1981) who reports that a majority of US and Swedish students consider themselves better drivers than their peers. The interpretation in our case is not as straightforward, however. First, the peer group – the "average investor" – is not as clearly defined. While the sample investors are probably better informed than the typical German investor who holds some type of equity (including company stock and stock mutual funds), they are on average much less informed than the professional investors they are likely trading with in the marketplace. Second, even if one accepts relative knowledge as a proxy for overconfidence, it is unclear whether overconfidence about knowledge translates into overconfidence about portfolio choices. Notwithstanding these reservations, relative knowledge – or the discrepancy between perceived knowledge and actual knowledge, defined as the residual of a regression of perceived knowledge on length of experience, actual knowledge inferred from the quiz performance, and actual knowledge inferred from the respondent's risk assessment – seems to be an attractive proxy for overconfidence. After all, respondents who claim to be much more knowledgeable than the typical investor, or those who overestimate how much they know, may not be aware of the identity of the counterparty to the trade or underestimate the counterparty – likely a professional investor with access to vastly superior resources. Yet such an awareness is key to no-trade theorems (see, e.g., Milgrom and Stokey (1982) and Tirole (1982)).

3.2.3. *Risk aversion*

One would expect measures of risk aversion to be systematically related to portfolio choices such as portfolio volatility. And, although both risk-averse and risk-tolerant investors should hold a well-diversified portfolio of financial assets, there is evidence that some investors are unable to distinguish systematic from unsystematic risk (see, e.g., Kroll et al. (1988) and Siebenmorgen and Weber (2001)); risk tolerant investors may thus be willing to take on more of both types of risk, leaving their portfolios less diversified. Moreover, people might trade into and out of equities in response to *changes* in risk aversion. However, the high frequency with which many sample investors trade into and out of individual stocks while leaving their overall exposure to equities roughly constant, can hardly be explained by changes in risk aversion. Another possibility is that most of the trading is done for speculative purposes, i.e., people act on a signal about the difference between current and future prices of an asset. Models à la Grossman (1976) or Varian (1989) suggest that the greater someone's risk aversion, the smaller the change in the investor's position resulting from the signal, other things equal.

Survey respondents indicate their risk aversion on a four-point scale from “not at all willing to bear high risk in exchange for high expected returns” to “very willing to bear high risk in exchange for high expected returns”.[5]

Table VI documents the characteristics of respondents grouped by self-assessed risk aversion. Males are disproportionately represented in the least risk-averse group; about 95% of the least risk-averse investors are men as opposed to 85% in the most risk-averse group. The least risk-averse investors are also substantially younger than their risk-averse counterparts – 37 years of average age versus 45 years. Self-employment is negatively correlated with risk aversion.[6]

Column (1) of Table VII contains the results from an ordered probit regression of risk aversion on demographic and socio-economic investor attributes. Other things equal, younger and self-employed investors are less risk-averse, confirming the sign and significance of the univariate correlations. Male investors also tend to report to be less risk-averse, although the effect of gender is not robust to including the proxies for investor sophistication and for drivers of overconfidence (see Column (2) of Table VII). With the exception of perceived knowledge, all measures of investor sophistication and overconfidence are negatively correlated with self-reported risk aversion, most of them significantly so. In particular, respondents who report to know more than their peers and those who do well on the knowledge quiz think themselves risk-tolerant.

Kapteyn and Teppa (2002) report that subjective measures of risk aversion constructed from answers to this type of survey questions can explain considerable variation in self-reported portfolio choices. If the measure of risk aversion were a good proxy for the respondents’ risk preferences, one would expect it to be positively correlated with the riskiness of the respondents’ portfolios of financial and non-financial assets. Survey participants report the fraction of wealth invested across different asset classes. The fraction of wealth invested in non-fixed income financial securities, that is, the sum of allocations to stocks, mutual funds, and options (“risky assets”) is a simple measure of the riskiness of the self-reported wealth profile. Column (3) of Table VII contains the results of regressing the fraction of risky assets on demographic and socio-economic investor attributes, and Column (4) reports the results of a similar regression with proxies for investor sophistication, overconfidence, and risk aversion as additional explanatory variables. The coefficient on risk aversion is highly significant, both in statistical and in economic

[5] The U.S. Survey of Consumer Finances elicits the risk aversion of its respondents in a similar manner, by asking “Which of the statements on this page comes closest to the amount of financial risk that you are willing to take when you save or make investments?”, letting survey participants indicate one of the following: (1) “[. . .] take substantial financial risks expecting to earn substantial returns”, (2) “take above average financial risks expecting to earn above average returns”, (3) “take average financial risks expecting to earn average returns”, and (4) “not willing to take any financial risks”.

[6] Except for the lack of correlation between education and risk aversion, the univariate correlations between sample investor characteristics and risk aversion resemble those documented for the sample of 1998 SCF households with brokerage accounts.

Table VI. Self-reported risk aversion of different investor groups

The table reports demographic and socio-economic attributes of the sample investors grouped by self-assessed risk aversion. Group 1 consists of the most risk averse investors. Means or proportions are reported in the first row for each group. When applicable, standard deviations are reported in the second row for each group. The last row of the table reports the statistical significance of mean or proportion comparison tests between groups 1 and 4; ***/**/* indicate that the means or proportions are significantly different at the 1%/5%/10% level.

Self-reported Risk aversion	(1) Fraction of respondents	(2) Gender [% male]	(3) Mean age [years]	(4) College degree [%]	(5) Self-employed [%]	(6) Income Mean [DEM]	(7) Wealth Mean [DEM]
1 (Least RA)	17%	95%	37	69%	22%	93,000	336,000
			10			54,000	322,000
2	30%	92%	40	72%	17%	92,000	358,000
			11			48,000	321,000
3	39%	87%	41	69%	16%	95,000	370,000
			11			46,000	325,000
4 (Most RA)	14%	85%	45	74%	13%	94,000	438,000
			13			51,000	348,000
Most RA – Least RA		***	***		**		***

Table VII. Self-reported investor attributes versus self-reported risk postures

Unless otherwise mentioned, all attributes are defined as in Figures 1 and 2. *Riskfrac* is the fraction of wealth invested in non-fixed income financial securities (i.e., the sum of allocations to stocks, mutual funds, and options divided by self-reported wealth including real estate) calculated from survey responses. ln denotes the natural logarithm. Standard errors are in parentheses. Note: ***/**/* indicate that the coefficient estimates are significantly different from zero at the 1%/5%/10% level.

Dependent variable	(1) Risk aversion	(2) Risk aversion	(3) Riskfrac	(4) Riskfrac
Constant			1.284***	1.194***
			(0.084)	(0.133)
Gender	−0.207*	−0.123	0.051	0.040
	(0.123)	(0.125)	(0.035)	(0.034)
Age	0.019***	0.018***	−0.002**	−0.002
	(0.004)	(0.004)	(0.001)	(0.001)
College	0.115	0.131	0.026	0.035
	(0.078)	(0.080)	(0.022)	(0.022)
Self-employed	−0.287***	−0.298***	−0.013	−0.022
	(0.093)	(0.094)	(0.026)	(0.026)
ln(Income)	−0.094	−0.101	−0.051***	−0.052***
	(0.067)	(0.067)	(0.019)	(0.018)
ln(Wealth)	0.000	0.070*	−0.082***	−0.085***
	(0.035)	(0.038)	(0.010)	(0.010)
Experience		−0.017*		0.001
		(0.010)		(0.003)
Actual knowledge		−0.089***		0.018**
(quiz)		(0.031)		(0.009)
Actual knowledge		−0.036		−0.017
(risk)		(0.075)		(0.020)
Perceived knowledge		0.009		−0.006***
		(0.008)		(0.002)
Relative knowledge		−0.255***		0.038**
		(0.064)		(0.018)
Self-attribution bias		−0.094*		0.003
		(0.054)		(0.015)
Illusion of control		−0.106		0.055**
		(0.085)		(0.023)
Risk aversion				−0.042***
				(0.011)
Ancillary statistics				
Nobs	947	947	947	947
Pseudo R^2	1.9%	4.3%	21.1%	27.5%

terms; the least risk-averse investors hold almost twice the fraction in risky assets as their most risk averse peers, other things equal.

4. Self-Reported Versus Actual Behavior

4.1. DETERMINANTS OF POOR DIVERSIFICATION

Thus far, our analysis has relied on self-reported information. Merging the survey data with the brokerage transaction records allows us to contrast self-reported and actual behavior. Specifically, one can ask whether self-reported risk aversion is positively correlated with actual risk taking and whether investors who could be judged sophisticated by their self-reported attributes are actually better diversified. The clients' survey responses and trading records reveal investor and portfolio attributes that reflect different aspects of investor sophistication. In addition, an investor's tendency to prefer nearby stocks – either a preference for domestic over foreign stocks (home bias) or a preference for local domestic over remote domestic stocks (local bias), or both – can be interpreted as a lack of sophistication (see also Huberman (2001), Grinblatt and Keloharju (2001), and Zhu (2002)). Proxies for the home bias and the local bias can be readily calculated as the account fraction invested in German stocks and mutual funds investing in German stocks, and the distance between the investor and his portfolio relative to the distance between the investor and the market portfolio.[7] The local bias measure, pioneered by Coval and Moskowitz (1999), is defined as follows:

$$LB_i \equiv \sum_{j=1}^{N} \left(m_j - h_{i,j}\right) \frac{d_{i,j}}{d_i^M} = 1 - \frac{\sum_{j=1}^{N} h_{i,j} d_{i,j}}{d_i^M} \tag{1}$$

where $d_i^M \equiv \sum_{j=1}^{N} m_j d_{i,j}$, m_j is the weight of stock j in the benchmark (market) portfolio, $h_{i,j}$ is the weight of stock j in investor i's portfolio, and $d_{i,j}$ is the distance between investor i and firm j. If investors with a preference for the familiar indeed bought and held just a few near-by stocks as conjectured by Huberman (2001), one would expect the home and local bias measures to be negatively correlated with account diversification.

In the mean-variance framework of portfolio theory, the portfolio's aggregate volatility is the only measure of risk an investor should be concerned with. Portfolio volatility is measured as the annualized standard deviation of daily portfolio returns from the day the account was opened until May 31, 2000 or when the account was closed, whichever comes first. Figure 3 shows a histogram of annualized portfolio volatility. The distribution is skewed to the right with a median portfolio volatility of 30% and an average of 35%; the DAX 100, a broad index of German stocks, has

[7] Given latitude (lat) and longitude (lon) coordinates for respondent i and firm j, the distance between i and j is calculated as $d_{i,j} = earth\ radius \cdot acos(sin\ (lat_j) sin(lat_i) + cos(lat_j) cos\ (lat_i)\ cos(lon_j - lon_i))$.

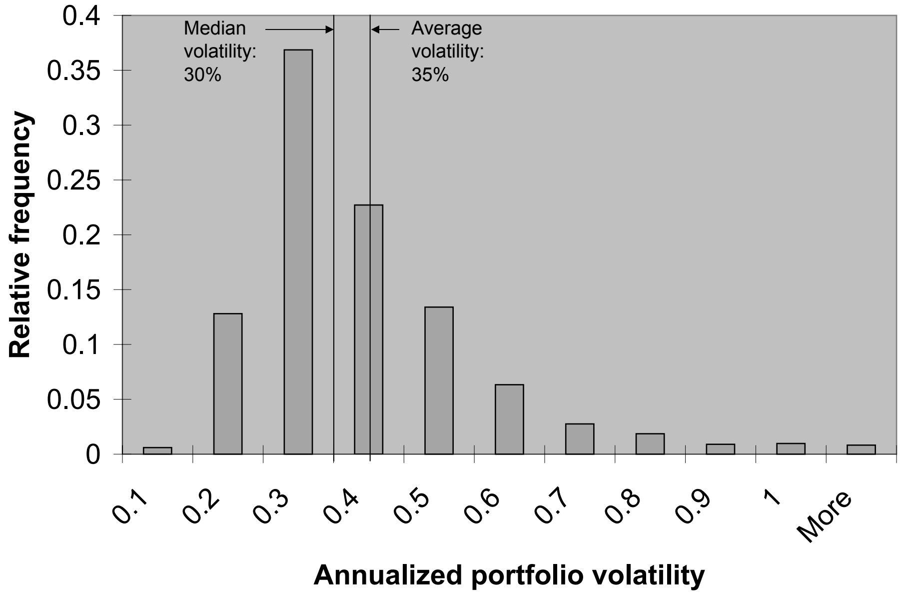

Figure 3. Histogram of annualized portfolio volatility.

an annual volatility of 20% during the sample period. Columns (1)–(3) of Table VIII report the estimates from regressions of the logarithm of portfolio volatility on different sets of investor attributes: objective attributes such as gender and wealth, subjective attributes such as perceived knowledge, and investor attributes inferred from portfolio statistics such as a preference for the familiar. The relations between the independent variables income, wealth, and portfolio size, and the dependent variable portfolio volatility are likely non-linear and we thus log these independent variables as regressors. For example, portfolio volatility is expected to decrease in portfolio size, but at a decreasing rate if only because of fixed transaction costs. We also log portfolio volatility as it is bounded below by zero and skewed to the right. Although the income, wealth, relative knowledge, and risk aversion variables are elicited as categorical variables (see Appendices E and F), we include them as continuous variables. As a robustness check, we consider alternative specifications with full sets of dummy variables instead of continuous variables (e.g., substituting the risk aversion score with three dummy variables representing answers on the ordinal four-point risk aversion scale (see Section 3.2.3)). The results discussed below are qualitatively robust to the different specifications.

Column (1) of Table VIII shows that younger, self-employed, and less wealthy investors hold more volatile portfolios. Including the subjective attributes as explanatory variables roughly doubles the R^2 of the regression (see Column (2) of Table VIII). Self-reported risk aversion, the single most important explanatory variable in the regression, is strongly negatively correlated with portfolio volatility; going from the most risk-averse to the least risk-averse category is associated with

Table VIII. Determinants of portfolio diversification

Unless otherwise mentioned, all attributes are defined as in Figures 1 and 2. The log of portfolio volatility, the dependent variable in Columns (1)–(3), is calculated using monthly returns during the entire period the account is open. The log of the Herfindahl-Hirschmann Index, the dependent variable in Columns (4)–(6), is calculated as of 5/31/2000 (or as a period average for accounts that are closed before the end of the sample period). The standard errors in parentheses are corrected for heteroskedasticity as suggested by White (1980). Note: ***/**/* indicate that the coefficient estimates are significantly different from zero at the 1%/5%/10% level.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	ln(Vol)	ln(Vol)	ln(Vol)	ln(HHI)	ln(HHI)	ln(HHI)
Constant	−0.436***	0.122	0.447**	−0.428	1.724**	2.366***
	(0.115)	(0.188)	(0.191)	(0.406)	(0.695)	(0.664)
Gender	0.024	0.028	0.036	−0.257	−0.231	−0.120
	(0.055)	(0.054)	(0.052)	(0.162)	(0.169)	(0.143)
Age	−0.007***	−0.005***	−0.004***	−0.019***	−0.020***	−0.014***
	(0.001)	(0.002)	(0.001)	(0.005)	(0.006)	(0.005)
College	−0.030	−0.002	−0.006	−0.149	−0.057	−0.039
	(0.030)	(0.029)	(0.028)	(0.112)	(0.112)	(0.103)
Self-employed	0.092**	0.060	0.056	0.066	0.005	0.004
	(0.038)	(0.037)	(0.035)	(0.133)	(0.133)	(0.116)
ln(Income)	−0.011	−0.017	−0.015	−0.047	−0.072	−0.114
	(0.027)	(0.025)	(0.023)	(0.092)	(0.091)	(0.079)
ln(Wealth)	−0.073***	−0.049***	−0.004	−0.125**	−0.077	0.157***
	(0.014)	(0.014)	(0.015)	(0.052)	(0.056)	(0.057)
Experience		−0.012***	−0.011***		0.011	0.012
		(0.003)	(0.003)		(0.014)	(0.012)

Table VIII. Determinants of portfolio diversification (continued)

Dependent variable	(1) ln(Vol)	(2) ln(Vol)	(3) ln(Vol)	(4) ln(HHI)	(5) ln(HHI)	(6) ln(HHI)
Actual knowledge		0.010	0.016		−0.008	0.003
(quiz)		(0.012)	(0.012)		(0.047)	(0.041)
Actual knowledge		0.000	0.003		−0.306***	−0.271***
(risk assessment)		(0.028)	(0.027)		(0.104)	(0.095)
Perceived knowledge		−0.010***	−0.011***		−0.027**	−0.024**
		(0.003)	(0.003)		(0.012)	(0.011)
Relative knowledge		0.025	0.034		−0.036	0.036
		(0.023)	(0.023)		(0.091)	(0.083)
Self-attribution bias		0.024	0.024		0.003	0.006
		(0.020)	(0.019)		(0.074)	(0.065)
Self control		−0.046	−0.034		−0.113	−0.083
		(0.033)	(0.031)		(0.124)	(0.110)
Risk aversion		−0.124***	−0.113***		−0.248***	−0.190***
		(0.015)	(0.014)		(0.056)	(0.051)
Local bias			−0.024			0.511***
			(0.053)			(0.161)
Home bias			0.087**			1.429***
			(0.043)			(0.159)
ln(Portfolio size)			−0.075***			−0.336***
			(0.011)			(0.039)
Ancillary statistics						
Number of observations	874	874	874	874	874	874
R^2	11.3%	20.6%	25.6%	4.8%	8.9%	18.5%

an increase in annual portfolio volatility from 26% to 39%, holding other investor attributes constant. By itself, cross-sectional variation in risk aversion explains more than 9% of the total cross-sectional variation in portfolio volatility. Given that risk aversion is reported on an ordinal scale, its explanatory power is remarkable. One explanation is that the observed investors use the same information channels or interact in chat rooms and therefore perceive risk similarly (even though they have different preferences for risk). Length of experience and perceived knowledge are also strongly negatively correlated with portfolio volatility; a one-standard deviation increase in experience or perceived knowledge is associated with a volatility decrease from 32% to 30%, other things equal. The relevance of the subjective attributes is unaffected by including the proxies for the local and home biases and log portfolio size (see Column (3) of Table VIII). Investors with smaller accounts and those with a greater preference for domestic stocks hold more volatile portfolios. In part, the positive correlation between the proxy for the home bias and volatility is due to a greater reluctance to delegate investment decisions; investors with a preference for domestic stocks hold a smaller fraction of their equities in mutual funds. Neither of the proxies for drivers of overconfidence is significantly related to portfolio volatility.

While portfolio volatility might be the most relevant measure of risk an investor should be concerned with, it is by no means clear that individual investors actually pay attention to aggregate volatility as opposed to other risk measures (see, e.g., Kroll et al. (1988), Kroll and Levy (1992), and Siebenmorgen and Weber (2001)). Holding more positions is arguably the easiest way to become better diversified. The extent of portfolio concentration can be captured by the Herfindahl-Hirschmann Index (HHI), defined as

$$\mathrm{HHI} \equiv \sum_{i=1}^{n} w_i^2 \tag{2}$$

where w_i is the portfolio weight of stock i and one tenth of the portfolio weight of stock fund i. Underlying the weight assigned to stock funds is the assumption that each fund holds 100 equally-weighted positions that do not appear in another holding of the investor. The index lies between zero and one; higher values indicate less diversified portfolios. The index value for a portfolio of n equally-weighted stocks is $\frac{1}{n}$.[8] An investor whose entire portfolio consists of one mutual fund has an HHI of 0.01; an investor holding two mutual funds has an HHI of 0.005. The HHI is probably the most salient of the risk measures and its calculation the most reliable since it does not rely on any assumptions about the stochastic process that generates returns. Using all available holdings data for the survey respondents, the mean period-average HHI value is found to be 0.32, corresponding to an equally

[8] Blume and Friend (1975) motivate the HHI as a measure of how closely an individual portfolio approximates the market portfolio: $\sum_{i=1}^{N}(w_i - w_i^m)^2 \approx \sum_{i=1}^{N} w_i^2 \equiv HHI$, since the market weights of individual stocks are small.

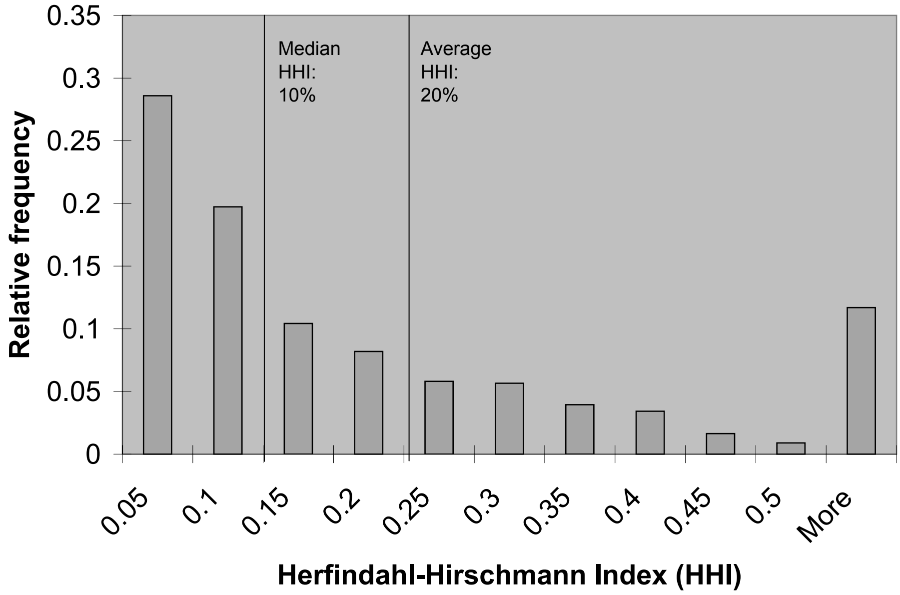

Figure 4. Histogram of end-of-period HHI.

weighted position in little more than three individual stocks. In May 2000, at the end of the sample period, the average HHI is 0.2 which corresponds to an equally weighted position in five individual stocks. The typical HHI of a portfolio is only 0.1, however, indicating that the distribution of HHIs is skewed to the right (see Figure 4).

Columns (3)–(6) of Table VIII report the estimates from regressions of the logarithm of HHI on the same set of investor attributes used to explain cross-sectional variation in portfolio volatility. The coefficient estimates are qualitatively similar to those obtained in the volatility regression, with few exceptions. Again, the explanatory power of the regression nearly doubles when subjective investor attributes are considered in addition to the demographic and socio-economic attributes (see Column (4)). Risk aversion as well as actual knowledge inferred from investor risk assessments and perceived knowledge are negatively correlated with portfolio concentration (see Column (5)). In contrast to the volatility regressions, the local bias measure is strongly positively correlated with the dependent variable – more locally biased clients hold concentrated portfolios of nearby stocks, consistent with the familiarity hypothesis (see Column (6)). Account size is strongly negatively correlated with portfolio volatility. Other things equal, wealth is positively correlated with portfolio volatility. An entertainment account effect might be at work here: for a given account size, an increase in wealth means that the observed portfolio becomes a less important piece of the investor's wealth.

One concern is that the analysis in Table VIII is plagued by a specification error due to sample selection. Although portfolio attributes such as volatility can be calculated for all the clients invited to participate in the survey – whether they choose to participate or not – the subjective investor attributes as well as many demographic and socio-economic attributes are only available for participants. We therefore re-estimate the regressions using the two-step procedure suggested by Heckman (1979), but none of the above inferences change as a result.[9] We also consider the possibility that investors increase their risk exposure following periods of high returns by regressing log portfolio volatility, calculated for the period January 2000-May 2000, on investor attributes and lagged portfolio returns, calculated for the period January 1999–December 1999 (see also Thaler and Johnson (1990) and Massa and Simonov (2005)). Lagged portfolio returns are positively correlated with end-of-sample volatility, but the correlation turns insignificant once we control for lagged portfolio volatility as well; thus, the correlation could be an artifact of persistently volatile stocks such as technology stocks doing well in 1999.

In summary, subjective investor attributes help explain the substantial variation in individual risk postures. In particular, both self-reported and actual risk postures correspond well to self-reported risk aversion. In addition, more sophisticated investors appear to make better portfolio choices; other things equal, those who report to be more experienced, knowledgeable, or are actually more knowledgeable, are also better diversified. By contrast, there is no evidence that investors who might be subject to an illusion of control or a self-enhancing attribution bias – and thus more overconfident – take bolder positions.

4.2. DETERMINANTS OF PORTFOLIO CHURNING

Every month, the sample investors turn over more than one sixth of their portfolio, on average – average monthly turnover is defined as one plus the sum of purchases and sales during the number of months the account has been active (active months), divided by twice the period-average portfolio value times the number of active months. Figure 5 shows that the distribution of average monthly turnover across clients is substantially skewed to the right, but even the typical client turns over his portfolio at a rate of almost 9% per month – about once every year. The group of the most aggressive traders earns significantly lower portfolio returns than the least aggressive traders; before transaction costs, however, their performance is similar – aggressive trading hurts portfolio performance because trading is costly (see Barber and Odean (2000) for a similar result).

Traditional finance theory shows that there is little room for speculative trading among rational agents (see, e.g., Milgrom and Stokey (1982) and Tirole (1982)). Moreover, non-speculative trading should occur in portfolios rather than individual stocks (see, e.g., Subrahmanyam (1991) and Gorton and Pennacchi (1993)). Given this theoretical perspective and the high cost of trading, active trading in individual stocks is puzzling (unless perhaps it involved shorting employer stock, the oppos-

[9] Detailed results of the first- and second-stage regressions are available from the authors upon request.

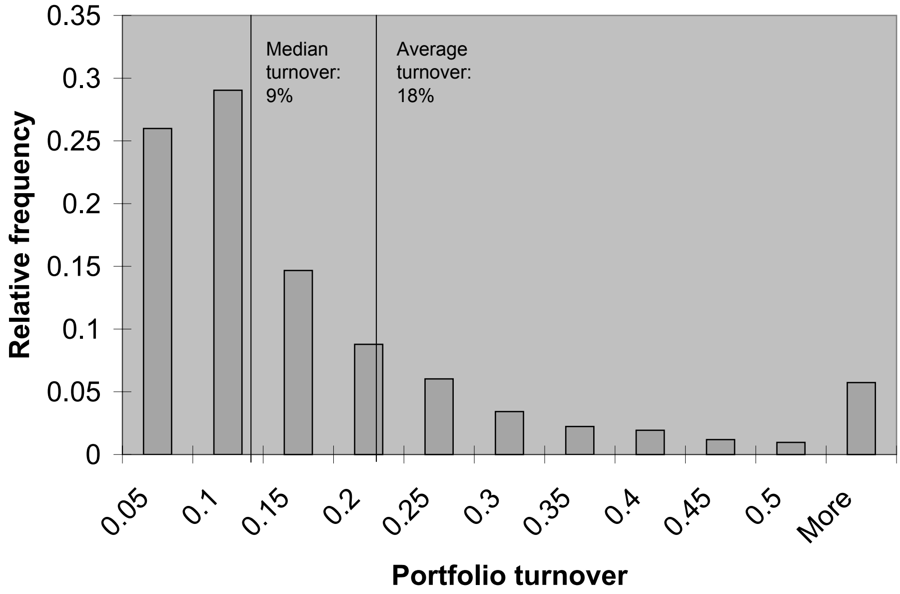

Figure 5. Histogram of monthly portfolio turnover.

ite of which is observed (see Huberman and Sengmüller (2004))). Examining the determinants of the cross-sectional variation in portfolio turnover will help inform new theories to explain the observed trading volume. If aggressive trading were due to decision-making biases arising from lack of sophistication or overconfidence (see Odean (1998)), one would expect portfolio turnover to be negatively correlated with measures of investor sophistication and positively correlated with more direct measures of overconfidence such as those constructed in Section 3.2.2 of this paper.

To analyze the multivariate relations between portfolio turnover and investor characteristics, we regress the logarithm of average monthly turnover estimated across all observations for an account on a similar set of investor attributes as in the portfolio risk regressions. Table IX contains detailed results. When we confine our attention to demographic and socio-economic variables, the age and gender findings reported in Barber and Odean (2001) obtain: Column (1) of Table IX shows that, other things equal, younger respondents and male respondents trade more actively than their older and female counterparts. Moreover, wealthier investors churn their portfolios less. At first glance, this seems to be at odds with Vissing-Jørgensen (2003), who finds that wealthier households report placing more trades, using responses from the 1998 and 2001 Survey of Consumer Finances. Wealthier investors in our sample also place more trades, but they turn over their portfolios less frequently, other things equal. Portfolio turnover is a better measure for churning because it reflects the magnitude of trading relative to the portfolio size; investors who save for retirement by splitting a fraction of their income every month among a few mutual funds, for example, are likely to be classified as heavy traders when trading activity is measured by the number of trades.

Column (2) of Table IX reports the results of a similar regression with the variables constructed from the survey as additional explanatory variables. As in the portfolio risk regression, the inclusion of subjective investor attributes greatly improves the explanatory power of the regression; the R^2 jumps from 6.6% to 17.3%. Less risk-averse respondents turn over their portfolio more aggressively; going from the most risk-averse to the least risk-averse category is associated with an increase in monthly portfolio turnover from 6% to 15%, holding other investor attributes constant. Note that the inference is quantitatively similar when risk aversion is modelled non-linearly, i.e., as three dummy variables reflecting the respondent's answer on the ordinal four-point scale. Investors who could be deemed more sophisticated by their displayed knowledge trade more aggressively. This result should be cautiously interpreted as it is possible that investors acquire knowledge about financial markets through trading. The interpretation of relative knowledge being positively correlated with turnover is less ambiguous – if an investor believes that he is better informed about the securities he trades than his counterparty, he may be more likely to trade.[10] To the extent that he is likely to trade with a well-informed market maker or other professional investor, such a belief could be interpreted as overconfidence. By contrast, the two proxies for drivers of overconfidence fail to explain cross-sectional variation in trading intensity. Consistent with Gervais and Odean (2001), survey respondents with longer investment experience trade substantially less; a one-standard deviation increase in experience is associated with a decrease in monthly turnover from 9.5% to 8%, other things equal.

Consistent with Huberman's (2001) conjecture, investors with a preference for the familiar – as measured by the distance between the investor and his portfolio relative to the distance between the investor and the market portfolio – appear content to buy *and hold* a few local stocks (see Column (3) of Table IX). It is possible that holdings of company stock also help explain the observed correlation between local bias and portfolio turnover.[11] At a minimum, the correlation between local bias and portfolio turnover suggests that individual investors do not hold local stocks to exploit real or imagined informational advantages; if this were the case,

[10] In an unreported regression, we include an alternative relative knowledge variable: the discrepancy between perceived knowledge and actual knowledge measured as the residual from a regression of perceived knowledge on experience and the two measures of actual knowledge (see Section 3.2.2). The coefficient estimate is not significantly different from zero.

[11] We thank an anonymous referee for pointing this out. Large publicly traded German companies have employee share purchase programs where employees can buy company stock at a discount if they commit to holding the shares for a certain period, mostly between one and five years. We suspect that the incidence of restricted holdings in our sample is very limited, however, since such shares are typically held by the company on behalf of their employees in an aggregate account at no cost to the employee.

Table IX. Determinants of portfolio turnover

Columns (1)–(3) report the results of OLS regressions of the logarithm of average monthly turnover on investor and portfolio attributes. Turnover is defined as one plus the sum of purchases and sales divided by the period-average portfolio value. Average monthly turnover is turnover divided by the number of months the account has been active. In Column (4), only trading volume deemed speculative is considered in the turnover calculation. See Figures 1 and 2 for a definition of the attributes. *ln* denotes the natural logarithm. The standard errors in parentheses are corrected for heteroskedasticity as suggested by White (1980). Note: ***/**/* indicate that the coefficient estimates are significantly different from zero at the 1%/5%/10% level.

Dependent variable	(1) ln(Turnover)	(2) ln(Turnover)	(3) ln(Turnover)	(4) ln(Speculative turnover)
Constant	−0.883***	−1.239***	−1.231***	−7.962***
	(0.295)	(0.462)	(0.463)	(1.926)
Gender	0.310***	0.249**	0.242**	1.295**
	(0.115)	(0.108)	(0.109)	(0.563)
Age	−0.010***	0.000	0.000	0.011
	(0.004)	(0.004)	(0.004)	(0.015)
College	−0.008	−0.008	−0.004	−0.044
	(0.073)	(0.067)	(0.067)	(0.293)
Self-employed	0.218**	0.142*	0.133	−0.139
	(0.089)	(0.084)	(0.084)	(0.354)
ln(Income)	0.019	0.016	0.031	0.123
	(0.068)	(0.063)	(0.064)	(0.279)
ln(Wealth)	−0.146***	−0.143***	−0.139***	−0.218
	(0.033)	(0.033)	(0.033)	(0.138)
Experience		−0.032***	−0.032***	−0.056
		(0.009)	(0.009)	(0.035)
Actual knowledge		0.054*	0.058**	0.376***
(quiz)		(0.028)	(0.028)	(0.119)
Actual knowledge		0.165**	0.150**	0.344
(risk assessment)		(0.065)	(0.065)	(0.275)
Perceived knowledge		−0.001	−0.001	−0.026
		(0.008)	(0.008)	(0.030)
Relative knowledge		0.123**	0.116*	0.553**
		(0.060)	(0.059)	(0.242)
Self-attribution bias		−0.024	−0.021	−0.166
		(0.049)	(0.049)	(0.194)
Self control		0.075	0.076	0.620*
		(0.072)	(0.072)	(0.316)
Risk aversion		−0.292***	−0.291***	−0.689***
		(0.037)	(0.037)	(0.140)
Local bias			−0.242**	−0.705*
			(0.099)	(0.416)
Home bias			−0.052	−1.625***
			(0.109)	(0.439)
Ancillary statistics				
Number of observations	874	874	874	874
R^2	6.6%	17.3%	17.9%	10.9%

one would expect them to aggressively buy and sell in response to signals rather than buy and hold.

To address the concern that differences in turnover might be primarily due to differing non-speculative motives such as differing savings rates and liquidity needs, rebalancing activities, and tax-loss selling, we estimate an alternative turnover measure excluding "non-speculative" trades. To that end, we extend the definition of speculative trades proposed by Barber and Odean (2002) as follows. The transaction records indicate whether a transaction is part of an automatic investment or an automatic withdrawal plan that exist for more than one hundred individual stocks and mutual funds. Such transactions are likely driven by savings motives and are excluded. Next, we only count speculative sales and purchases that follow within three weeks of speculative sales. To be classified as speculative, sales transactions have to meet all of the following criteria: 1. they are followed by a purchase within three weeks (to exclude liquidity-driven sales), 2. they are made for a profit (to exclude tax-loss sales), and 3. the sell order is for the entire position (to eliminate rebalancing sales). The results from regressing the modified turnover measure on investor and portfolio attributes are shown in Column (4) of Table IX. The earlier inferences regarding the relation between the investor's risk aversion and turnover and between actual/relative knowledge and turnover become even sharper. The degree to which respondents feel in control over their investments is marginally positively correlated with speculative turnover.

To check whether the results are affected by sample selection, we re-estimate the turnover regressions using Heckman's (1979) two-step procedure. The results are quantitatively similar to those without the correction for selection bias.

In sum, self-reported risk aversion is the most successful attribute in explaining variation in turnover. This suggests that overconfidence has a limited role in explaining differences in the propensity to trade.

5. Conclusion

The neoclassical approach has not adequately explained the huge trading volume and the widespread lack of diversification observed in individual investor portfolios. The behavioral approach offers some hope of doing just that; however, it will not be easy. Behavioral hypotheses such as "overconfidence causes trading" are theoretically appealing but empirically hard to assess because the underlying personal attributes are unobservable.

The existing empirical literature on investor behavior focuses on the relation between behavior and objective investor attributes such as age, gender, and income to test behavioral hypotheses. Such objective attributes are relatively easy to elicit but may capture little of the underlying psychological construct. Our paper departs from the prior literature by relating actual investor behavior to subjective attributes of investors – attributes that require the investor's assessment such as whether he is risk averse, knowledgeable about investments, or whether his investment gains and losses are due to skill or luck – as well as objective attributes.

When confining ourselves to objective attributes to explain investor behavior, we get results similar to those reported in earlier papers – e.g., younger and male investors trade more aggressively than older and female investors (Barber and Odean (2001)), and older or more experienced and better educated investors hold less concentrated portfolios (Goetzmann and Kumar (2002)).

The inclusion of subjective attributes offers several insights. The self-perception of investors revealed by their survey responses is fairly accurate. For example, investors who report to be more knowledgeable about financial securities do better on a quiz which tests such knowledge. The variation in self-reported risk aversion helps to explain the variation in actual risk taking measured by portfolio volatility and concentration. Perhaps more surprisingly, the variation in self-reported risk aversion also helps to explain the variation in portfolio turnover.

This paper is one of the first to confront actual investor behavior with both objective and subjective investor attributes. The paper uncovers a prominent role for self-reported risk aversion in explaining variation in investor behavior. By contrast, there is little evidence that differences in overconfidence are associated with differences in behavior. These results should be interpreted in light of the sample size, definition of proxies, and the cross-sectional nature of the analysis; larger samples, different proxies for overconfidence, and availability of panel data, may produce different results.

Given the present data, the appropriate conclusion is that risk attitudes of investors are key to understanding two of the most puzzling aspects of their behavior – poor diversification and high turnover. A better understanding of what shapes investor risk attitudes and perceptions thus appears to be a promising avenue of future research.

Appendix A. Questionnaire Design

The 11-page questionnaire covers the following areas:

1. General (2 questions)
    a. presence of other accounts
    b. motives for holding other accounts
2. Investment behavior (14 questions/ statements)
    a. investment motives
    b. investment strategies
3. Attitude towards investing and risk (68 questions/ statements)
    a. general risk
    b. investing
    c. (and d.) investment risk
4. Investment experience and knowledge (50 questions/ statements)
    a. length of experience
    b. perceived experience
    c. knowledge about different financial assets
    d. knowledge quiz
    e. risk assessment of different asset categories
5. Portfolio structure (20 questions/ statements)
    a. net worth
    b. allocation of wealth among different asset categories
    c. satisfaction with current portfolio
    d. intended changes to portfolio structure
6. Personal attributes (7 questions/ statements)
    a. gender
    b. age
    c. marital status
    d. presence and number of children
    e. employment
    f. education
    g. income

It takes about 25 minutes to carefully complete the questionnaire.

Appendix B. Experience and Perceived Knowledge

	4.A. Length of experience			
1	How long have you been investing?			
	❑	not at all	❑	5 to 10 years
	❑	up to 1 year	❑	10 to 15 years
	❑	1 to 3 years	❑	more than 15 years
	❑	3 to 5 years		

4.C. Your financial securities knowledge

In the following, we would like to ask you some questions in order to improve our information offering for you. Imagine that a friend asks you about different financial assets. How well can you explain them to him or her?

		Can explain very well	Can explain partially	Cannot explain well	Cannot explain at all	Don't know
1	Money market funds	❑	❑	❑	❑	❑
2	Savings account	❑	❑	❑	❑	❑
3	Bonds	❑	❑	❑	❑	❑
4	Bond funds	❑	❑	❑	❑	❑
5	Stocks	❑	❑	❑	❑	❑
6	Stock funds	❑	❑	❑	❑	❑
7	Index certificates	❑	❑	❑	❑	❑
8	Options and futures	❑	❑	❑	❑	❑
9	Real estate investment trusts	❑	❑	❑	❑	❑
10	Mutual fund-based cash value life insurance	❑	❑	❑	❑	❑
11	Cash value life insurance	❑	❑	❑	❑	❑

Appendix C. Actual Knowledge

	4.D. Your financial securities knowledge	
	Now we would like to test your financial securities knowledge. Please read the following statements and indicate whether you think they're right or wrong. Please be honest and do not look up definitions in a book. If you don't know an answer, check "Don't know".	
1	The M-Dax indexes the performance of 70 midcap stocks.	❑ Correct (X) ❑ Incorrect ❑ Don't know
2	A benchmark is a measure against which the performance of a fund or portfolio is compared.	❑ Correct (X) ❑ Incorrect ❑ Don't know
3	The higher the price-earnings ratio of a stock, the higher expected profits and/ or expected profit growth of the company.	❑ Correct (X) ❑ Incorrect ❑ Don't know
4	The closing price of stock on Monday was E100. Suppose an investor puts in an unlimited sales order on Tuesday. (S)He will never get a price below E100.	❑ Correct ❑ Incorrect (X) ❑ Don't know
5	Once the market price drops below an agreed-upon price level, a "stop-loss" order initiates a sale at the next quoted price.	❑ Correct (X) ❑ Incorrect ❑ Don't know
6	A bid price (Geldkurs) means: at the quoted price, there was positive supply, but no demand.	❑ Correct ❑ Incorrect (X) ❑ Don't know
7	Capital gains which are realized within the 12-month "speculation period" are only tax-exempt if they sum up to less than DEM 1,000 (for single investors). Realized gains exceeding DEM 1,000 are fully taxable - without deduction.	❑ Correct (X) ❑ Incorrect ❑ Don't know

Appendix D. Risk Assessment

4.E. Your risk evaluation of different asset categories

Risks are perceived differently by different people. In the following, we would like to know how risky you judge the asset categories listed below.

If you think that an asset category is "safe"/ not risky at all, then mark "1". If you think that an asset category is extremely risky, then mark "10". You can use the numbers between 1 and 10 to make more gradual statements.

	Asset category	your evaluation of risk associated with the asset category	Don't know
1	Money market funds	______	❏
2	Savings account	______	❏
3	Bonds	______	❏
4	Bond funds	______	❏
5	Stocks	______	❏
6	Stock funds	______	❏
7	Index certificates	______	❏
8	Options and futures	______	❏
9	Real estate	______	❏
10	Real estate investment trusts	______	❏
11	Mutual fund-based cash value life insurance	______	❏
12	Cash value life insurance	______	❏

(note: the actual questionnaire allows respondents to check numbers rather than to write them down)

Appendix E. Allocation of Total Wealth

5.A. Your wealth status

1 What does your current total wealth amount to?

(current total wealth: the current value of all your investments, life insurance and real estate holdings, i.e., including investments held outside your brokerage account at [...])

- ❑ none ➔ please proceed to question block 6
- ❑ up to DM 5.000,-
- ❑ DM 5.000,- to DM 10.000,-
- ❑ DM 10.000,- to DM 15.000,-
- ❑ DM 15.000,- to DM 20.000,-
- ❑ DM 20.000,- to DM 40.000,-
- ❑ DM 40.000,- to DM 60.000,-
- ❑ DM 60.000,- to DM 100.000,-
- ❑ DM 100.000,- to DM 150.000,-
- ❑ DM 150.000,- to DM 500.000,-
- ❑ DM 500.000,- to DM 1.000.000,-
- ❑ Greater than DM 1.000.000,-
- ❑ Current value unknown

2 You have presumably allocated your wealth across different asset categories (e.g., savings accounts, real estate, mutual funds, stocks, life insurance, etc.). We would like to know about this allocation in more detail.

(Please consider the current value of all investments belonging to a category, i.e., also those held outside your brokerage account at [...]. Example: your total wealth is DEM 100,000, invested in a mutual fund (the current value of this position is DEM 30,000 or 30% of your total wealth) and a life insurance (whose current cash value is DEM 70,000 or 70% of your total wealth).

	Asset category	Current fraction of your total wealth
1	Money market funds	❑❑❑ %
2	Savings account	❑❑❑ %
3	Bonds	❑❑❑ %
4	Bond funds	❑❑❑ %
5	Stocks	❑❑❑ %
6	Stock funds	❑❑❑ %
7	Index certificates	❑❑❑ %
8	Options and futures	❑❑❑ %
9	Real estate	❑❑❑ %
10	Real estate investment trusts	❑❑❑ %
11	Mutual fund-based cash value life insurance	❑❑❑ %
12	Cash value life insurance	❑❑❑ %

Appendix F. Demographic and Socio-economic Characteristics

	6. Personal questions	
	Kindly answer a few questions regarding yourself.	
1	Your gender?	❑ female ❑ male
2	Your age?	_ _ years old
3	Marital status?	❑ single ❑ married ❑ divorced ❑ widowed
4	Do you have children (if yes, how many)?	❑ no children _ _ children (please enter number)
5	To which job category do you belong?	❑ Retired ❑ Housewife/ -man ❑ Student ❑ Blue-collar ❑ White-collar ❑ Self-employed ❑ Civil servant ❑ Other ____________
6	What is your level of education or degree?	❑ Apprenticeship ❑ Advanced vocational degree ❑ College or University degree ❑ Other degree ❑ Other: ____________
7	What is your average gross annual income?	❑ No income ❑ up to DM 50.000,- ❑ DM 50.000,- to DM 75.000,- ❑ DM 75.000,- to DM 100.000,- ❑ DM 100.000,- to DM 150.000,- ❑ DM 150.000,- to DM 200.000,- ❑ greater than DM 200.000,-

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