Sensation Seeking, Overconfidence, and Trading Activity*

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January 9, 2008

ABSTRACT

This study analyzes the role that two psychological attributes—sensation seeking and overconfidence—play in the tendency of investors to trade stocks. Equity trading data from Finland are combined with data from investor tax filings, driving records, and mandatory psychological profiles. We use these data, obtained from a large population, to construct measures of overconfidence and sensation seeking tendencies. Controlling for a host of variables, including wealth, income, age, number of stocks owned, marital status, and occupation, we find that overconfident investors and those investors most prone to sensation seeking trade more frequently.

Keywords: Sensation Seeking, Overconfidence, Trading Activity

JEL classification: G110, G120

* We would like to thank the Finnish Vehicle Administration, the Finnish Armed Forces, the Finnish Central Securities Depository, and the Finnish Tax Administration for providing access to the data, as well as the Office of the Data Protection Ombudsman for recognizing the value of this project to the research community. Our appreciation also extends to Antti Lehtinen and Juan Prajogo, who provided superb research assistance, and to Narasimhan Jegadeesh, Samuli Knüpfer, Lisa Kramer, Juhani Linnainmaa, Tyler Shumway, Ivo Welch, and seminar participants at the Hong Kong University of Science and Technology, the University of Illinois, the London Business School, the London School of Economics, the University of Mannheim, the University of Michigan, Oxford University, the University of Texas, the University of Vienna, the SFM, and the Western Finance Association, who generated many insights that benefited this paper. We also thank Seppo Ikäheimo for his help in obtaining the data and Markku Kaustia, Samuli Knüpfer, Lauri Pietarinen, and Elias Rantapuska for participating in the analysis of the Finnish Central Securities Depository data. Finally, we are especially thankful for the detailed comments of an anonymous referee, an associate editor, and the editor, Campbell Harvey. Financial support from the Academy of Finland, the Foundation for Economic Education, and the Paulo Foundation is gratefully acknowledged.

Recently, empiricists have begun to study and document that behavioral attributes influence trading volume.[1] This evidence is compelling but it is difficult to conclusively argue that particular traits influence trading without better data. Much of the data used in the past to establish a connection between behavioral attributes and trading is experimental or aggregated across individuals. When actual trades are studied at the individual level, the results come from self-reported surveys, sometimes combined with brokerage trading records. These surveys and trading records often are based on a limited number of individuals, and sometimes have timing issues where performance and turnover affect an investor's desire to respond to the survey. They also tend to lack data on variables that might disparage claims of omitted variable or endogeneity biases as the source of the results. Even in the best case scenarios, control variables are self-reported, with no consequences for distortion by the reporting investor.

Even studies that avoid the inherent problems of surveys can leave many questions unanswered for lack of better data. As just one example, the seminal paper on overconfidence, Barber and Odean (2001), uses gender as an instrument for overconfidence. Since gender is related to trading—the portfolios of males exhibit greater turnover—they conclude that overconfidence is responsible for trading. Gender, however, is linked to a substantial number of other attributes that might affect trading. For instance, sensation seeking, a measurable psychological trait linked to gambling, driving, drug abuse, and a host of other behaviors, is more abundant in males. This variable, which is not controlled for in earlier studies, could account for some of the differences in trading activity between genders.

The contribution of this paper lies in being the first study to specifically focus on sensation seeking as a motivation for trade. It also is the first study to employ comprehensive data from a validated psychological assessment to directly measure overconfidence and analyze its relationship to trading. Using a comprehensive dataset from Finland, which offers what arguably might be the best set of control variables available for a study of this kind, we show that investors who are most prone to sensation seeking and those who are most overconfident trade the most. We now define these concepts.

Sensation seeking is a stable personality trait, studied in the psychology literature, which varies across individuals.[2] Those who are sensation seekers search for novel, intense, and varied experiences generally associated with real or imagined physical, social, and financial risks. The trait generates behaviors in many arenas that are less frequently observed among those endowed with lower degrees of the sensation seeking trait: These include risky driving, risky sexual behavior, frequent career changes, drug and alcohol abuse, participation in certain types of sports and leisure activities (like bungee jumping or roller coaster riding), and gambling.[3] Sensation seeking behavior crosses many domains; hence, a poker player or a traffic violator may show sensation seeking behavior in other arenas.[4] Trading fits the definition of a sensation seeking behavior. Participation in the stock market is perceived to be financially risky, but in the absence of trading, lacks novelty and variety. Gambling is also risky, but repeated gambling adds novelty and variety. A single bet may not be as satisfying to the sensation seeker as a series of smaller and distinct bets (even though the latter has less volatility).[5] It is the novelty of the new stock in one's portfolio, or the change in one's position in a stock that provides consumptive utility to the sensation seeker. Because of this, a diversified portfolio can be as stimulating to the sensation seeker as a non-diversified portfolio. However, a stale portfolio is not as exciting as a fresh one.

One could argue that a series of stock positions in a single stock is more stimulating to a sensation seeker than a diversified portfolio where one has minute changes to each position. This would mean that there are some stock investment behaviors that can be driven either by sensation seeking or by particular risk aversion parameters. Our analysis, however, is focused on trading per se, which (except for negligible rebalancing motivations) is not driven by risk aversion parameters.[6] Moreover, we control for the number of stocks in the investor's portfolio. Among all investors with the same degree of diversification, the sensation seekers should trade more.

Sensation seekers find trading entertaining, but that does not mean that those who find trading entertaining are sensation seekers. It is the variety, novelty, and perceived risk of trading that makes trading (as well as other sensation-related activities) entertaining. If trading is merely entertaining, in the same sense that television or golf is entertaining, there would be no difference in the proclivity to trade between sensation seekers and those who lack the trait. If trading is purely a leisure activity, those motivated by a relatively greater utility from leisure would trade the most frequently. We would observe that golfers and "couch potatoes" would trade the most, ceteris paribus. If trading is motivated by sensation seeking, those who take pleasure in sensation seeking activities—risky driving, drugs, risky sports, gambling, etc.—would trade the most.

Zuckerman (1994), one of the pioneers of the concept, developed an assessment scale for sensation seeking, for which we lack data. Our study makes use of a rare dataset as a substitute. We measure sensation seeking as the number of automobile speeding convictions earned by an investor over a multi-year period. Zuckerman (1994), as well as Jonah (1997), suggest that driving behavior may be one of the best observed behaviors for assessing sensation seeking. Data on speeding tickets from Finland is particularly pertinent with respect to the financial risks associated with this trait. In Finland, the fine for substantive automobile violations is a function of income. Thus, those who risk breaking the law do so under severe financial penalty as well as enduring possible physical risks.

Overconfidence is the tendency to place an irrationally excessive degree of confidence in one's abilities and beliefs. This definition has evolved into two different interpretations. The first is hubris or what is sometimes referred to as the "better than average effect." One can think of this as an irrational shift in the perceived mean. The other is "miscalibration." This arises when the confidence interval around the investor's private signal is tighter than it is in reality. This can be thought of as an irrational shift in perceived variance.

Both forms of overconfidence lead the overconfident investor to form posteriors with excessive weight on private signals. In the former case, the weight on one's private signals irrationally ignores Bayes rule and says "I am right;" in the latter case, Bayes' rule is known but not implemented properly because the variance parameter in the weight is incorrect. In either case, the private valuation of a stock will differ from that of the market as the overconfident investor places more validity on his private valuation and less on the market's valuation. This generates a larger willingness to trade than would be observed in a less confident investor. The link between overconfidence and trading activity has a recent theoretical and empirical literature behind it.[7]

We derive the overconfidence measure from a standard psychological assessment. This test is given to all Finnish males upon induction into mandatory military service. (Generally, this is at the age of 19 or 20, and, for most investors, it is many years prior to the trading activity we observe.) One of the scales from the test measures self-confidence. As this confidence measure is a combination of competence and overconfidence, we use regression analysis to control for competence and obtain overconfidence as the residual effect. Because of the mandatory and comprehensive nature of the psychological examination, the responses lack the bias typically associated with the decision of whether to answer a survey.[8] Our data are based on a scientifically designed assessment, not a survey. From the description and details we have obtained about the test, (which are largely confidential for obvious reasons), it appears as if few, if any of the questions are related to standard calibration assessment. The assessment is more geared to one's views of personal abilities, social image, and self-worth. Hence, after we take out competence, our overconfidence measure appears to be far closer to a better than average effect than to a miscalibration bias.[9]

The correlation between our sensation seeking and overconfidence measures is very low, so both behavioral attributes have relatively independent influence on trading. Sensation seeking is less related to the decision of whether to trade at all and more related to the decision of how much to trade. Although the number of trades is influenced by overconfidence, our analysis does not find a relationship between overconfidence and turnover. The lack of findings here (as in any study) could be due to noisy measurement. This also applies to the comparisons between sensation seeking and overconfidence.

Our paper also studies portfolio performance after transaction costs. Every investor group, sorted on the basis of its sensation seeking and overconfidence tendencies, exhibits negative performance after transaction costs. We measure performance as the returns of past buys less the returns of past sells for that investor group, adjusted for transaction costs. There is no support for a claim that trading is rational and profitable for any grouping of investors sorted on the basis of their psychological traits.

The paper is organized as follows: Section I offers motivation for the paper and describes the data. Section II presents the results on sensation seeking, overconfidence, and trading activity. It also includes a discussion of performance after transaction costs. Section III concludes the paper.

I. Motivation and Data

The literature in finance is ripe with stylized facts about investor behavior. One of the most prominent is that trading propensity is related to gender.[10] Figure 1 Panel A plots the average number of trades per year as a function of age and gender. Consistent with earlier findings, men trade more than women within all age groups. Panel B effectively offers the same plot but takes out the effect of income, wealth, and the number of stocks in the portfolio. It does this by plotting coefficients and sums of coefficients from a regression of a person's average number of trades on age dummies, the product of age dummies and a male gender dummy, and control variables for income and wealth deciles. The plot for females represents the coefficients on the age dummies; the plot for males represents the sum of the coefficient on the age dummy and the product of the age dummy and male gender dummy.

The relation between age and trading in Panel B differs a bit from that in Panel A. Except for very old and very young people, Panel A suggests that age has little effect on trading. By contrast, age is inversely related to trading for most ages in Panel B except for the very young. In both graphs, those under 23 at the start of the sample period experience a positive relationship between age and trading. This is expected: as one moves from the college (and military service) years to one's early career years, we would expect trading to increase. There also are large periods in the Panel A graph where age does not influence the gap in trading between men and women. The "gender gap" in trading is about the same for those born between 1940 and 1960, and it is wide in the middle while narrow at the tails. By contrast, when we control for income and wealth differences related to age and gender, Panel B indicates that the gender gap diminishes with age among those who are middle aged. Still, both panels indicate that males trade more than females, irrespective of age.

What lies behind the greater tendency of males to trade? One possibility, advanced by Barber and Odean (2001), is that males are more overconfident than females. Another is that males are more prone to sensation seeking, and thus enjoy the thrill of trading to a greater extent than females. Panel C plots the number of speeding tickets, a proxy for an investor's degree of susceptibility to sensation seeking, as a function of age and birth year. Except for those under 23 at the start of the trading sample period, there are similarities between the two graphs in Panels B and C. There is a gender gap in speeding tickets and it diminishes with age, provided one was born prior to or during 1973. Of course, for those born after 1973, particularly the youngest males, tickets diminish with age, quite dramatically, but trading in the stock market increases.

One has to be cautious about drawing conclusions from the similarities between Panels B and C. As Ameriks and Zeldes (2004) and others point out, it is very difficult to disentangle cohort, age, and time effects from each other. Still, the intriguing similarity between Panels B and C for those born before 1974 suggests that it might be interesting to run a horse race between sensation seeking and overconfidence if one had reasonable measures of these attributes for each investor. We are fortunate to be able to analyze such data.

A. Sensation Seeking

The classic characterization of sensation seeking is found in Zuckerman (1994, p. 27). He labels sensation seeking as "… a trait defined by the seeking of varied, novel, complex, and intense sensations and experiences, and the willingness to take physical, social, legal, and financial risks for the sake of such experience."

With respect to trading activity, sensation seeking is distinct from the magnitude or sign of the risk aversion parameter. For example, the willingness to take on an undiversified trading strategy may be encouraged by the consumptive value associated with sensation seeking, yet deterred by a high degree of risk aversion. The mix of these two competing forces may determine the degree of diversification. However, as Barber and Odean (2001) observe, an investor's risk aversion parameter has little bearing on desired trading frequency. The mere act of trading and the monitoring of a constant flow of "fresh stocks" in one's portfolio may create a more varied and novel experience than a buy and hold strategy, and it is likely to have adverse financial consequences because of trading costs, but it does not increase volatility *per se*.

Sensation seeking also appears to be distinct from the self-monitoring dimension studied by Biais et al. (2005).[11] Bell et al. (2000) analyzed what accounts for differences in risky behavior across groups of students who differed in their self-monitoring and sensation seeking tendencies. They found that any differences are largely accounted for by differences in the sensation seeking attribute. Group differences in risky behavior across the self-monitoring dimension are due to a correlation between the self-monitoring and sensation seeking attributes.

There is reason to believe that males are more prone to sensation seeking behavior.[12] As Zuckerman (1994) points out, males are more prone to risky sporting activities. While some of this may be explained by physical traits, there also is a greater tendency among males towards violence, alcohol, drugs, gambling, and most forms of illicit activity that is not as easily explained. Even relatively safe sensation seeking behaviors, like high speed amusement park rides, are more popular among males.[13] A review article by Jonah (1997) documents that sensation seeking is significantly related to risky driving.

Men also differ from women with respect to the type of gambling they do. Potenza et al. (2001) find that men prefer action-oriented forms of gambling, like blackjack, craps, or sports betting, as opposed to passive escape-oriented gambling (e.g., slot machines, lotteries). Biaszcynski et al. (1997) as well as Vitaro et al. (1997) suggest that action-oriented gambling reflects a higher level of sensation seeking among males. Comings (1998) shows that pathological gambling behavior may be transmitted genetically. Pavalko (2001, p. 34) likens trading (as opposed to investing) to action-oriented gambling.

B. Overconfidence

The second explanation we investigate for the greater trading of males is overconfidence. The literature suggests that there are significant gender differences in overconfidence, measured as a better-than-average effect. For example, Deaux and Farris (1977), Beyer and Bowden (1997), Beyer (1998), and Johnson et al. (2006) all find that men have higher self perceptions than women despite the general lack of difference in their test performance.[14]

To assess whether this form of overconfidence explains trading, it would be useful to directly observe a measure of overconfidence, rather than a measure that is tied to a gender-based instrument. We have overconfidence data on a large sample of subjects, assessed from an extensive psychological profile of those subjects. Our data also offer the possibility of a much cleaner test of whether overconfidence causes trading. Ideally, in a controlled experiment of whether overconfidence affects trading activity, all other attributes of the subjects would be identical and only overconfidence would vary. In a social science experiment, this ideal is not attainable. However, in our study, all of the subjects for whom we have a direct measure of overconfidence happen to be male. Moreover, the age at which we measure overconfidence is approximately the same across subjects (about 20). To demonstrate a link between such a measure of overconfidence and trading activity would indeed be remarkable, as it may imply that differences in overconfidence across individuals persist throughout one's lifetime and influence economic behavior. We also have data on a large number of control variables that allow us to use traditional regression analysis to assess overconfidence, with fewer concerns about omitted variables than one typically has in studies of economic behavior.

C. Data Sources

Our paper's analysis requires us to combine information from a number of datasets:

- FCSD data. This dataset records the portfolios and trading records from January 1, 1995 through November 29, 2002 of all household investors domiciled in Finland. The daily electronic records we use are exact duplicates of the official certificates of ownership and trades, and hence are very reliable. Details on this dataset, which includes trades, holdings, and execution prices, are reported in Grinblatt and Keloharju (2000, 2001). We study trading data from July 1, 1997 on for those individuals who held stocks at some point between January 1, 1995 and June 30, 1997. The latter requirement allows us to focus on the determinants of trading activity rather than on whether an investor participates in the stock market in the first place. (The results are qualitatively similar if we use all individuals in lieu of individuals who have invested in the market before.) In addition to trading data, we use this dataset to measure financial wealth and number of stocks held.
- HEX stock data. Closing transaction prices are obtained from a dataset provided by the Helsinki Exchanges (HEX). In combination with the FCSD data, this dataset is used to measure financial wealth and assess portfolio performance.

- FVA driver data. Data from the Finnish Vehicle Administration (FVA) were used to obtain a set of subjects who have a normal vehicle driving license (as opposed to a motorcycle or commercial driving license) as of July 1, 1997. The FVA data contain all driving-related final judgments on each motorist in the provinces of Uusimaa and East Uusimaa between July 1, 1997 and December 31, 2001. (These provinces contain Greater Helsinki and represent the most densely populated areas in Finland.) The judgments contain paragraphs about the nature of the violation that we coded either as "speeding related" or "not speeding related." Thus, we have comprehensive records of tickets for speeding that were finalized over a four and a half year period. [15] We use these data to measure differences in the sensation seeking attribute across investors. Driving record data is from drivers who both own and do not own a car. The data also contain car ownership records, which we use in a robustness test.[16]
- FAF psychological profile. This dataset, from the Finnish Armed Forces, helps us to measure cross-sectional variation in overconfidence among investors. Around the time of induction into mandatory military duty in the Finnish armed forces, typically at ages 19 or 20, males in Finland take a battery of psychological tests. It includes a leadership inventory test for which we have comprehensive data beginning January 1, 1982 and ending December 31, 2001. The leadership inventory assessment, which includes 218 "agree" or "do not agree" questions, provides eight scales for leadership. One of these scales is self-confidence, which is reported as a number from 1 to 9 (and is designed to approximate a stanine in the overall sample of test takers). The military's self confidence measure combines data from 30 different self confidence related questions. We convert this measure to an overconfidence measure using regression techniques described later in the paper for all shareholders who have

driver's licenses prior to July 1, 1997. The psychological profile also contains an intellectual ability score. The test measures intellectual ability in three areas: mathematical ability, verbal ability, and logical reasoning. FAF forms a composite ability score from the results in these three areas. We use the composite ability score in our analysis.

- FTA dataset. This dataset, from the Finnish Tax Administration, contains annual data from the 1998 and 1999 tax returns of Finnish investors in the provinces of Uusimaa and East Uusimaa, as well as data from a population registry. Variables constructed from this source include income, age, gender, marital status, occupation, and homeownership status. These variables are used as controls in regressions that explain trading activity and regressions used to construct a measure of overconfidence for an individual. We use 1998 data for all of the variables except for employment status, which is first reported in 1999.

D. Variable Description and Summary Statistics

Our analysis largely consists of cross-sectional regressions, with some measure of trading activity as a left hand side variable. The variables and the data sources for them are described in Table I Panel A. The remainder of the table provides summary statistics on the data. Panel B describes means, medians, standard deviations, and interquartile ranges for most of the variables. Panel C provides detailed summary statistics on the self-confidence measure. Panel D presents the correlation matrix for relevant variables.

As can be seen from Table I, Panel B, stock trades and speeding tickets are rare. Panel C's distribution of the self-confidence measure indicates that the highest and lowest measures of self-confidence (1 and 9) also are relatively rare. Our sample of male drivers is a bit more self-confident than the universe of males taking the assessment. Some of this may have to do with the fact that we limit our sample to individuals who own stocks between January 1995 and June 1997. Thus, our sample is wealthier than the population at large. Panel D indicates that the number of speeding convictions, self-confidence, and gender all have a fairly large correlation with various measures of a subject's trading activity, but self-confidence, described later, has a negligible correlation with the number of tickets earned.[17] Consistent with Figure 1 Panel A, age (without controls for income) does not display an obvious relationship with trading activity. Panel D also indicates that gender per se (with a dummy value of one being male) is more correlated with all measures of trading activity than are measures of sensation seeking and self-confidence. However, gender also is highly correlated with the sensation seeking attribute, as we hypothesized earlier.

II. Results

Our analysis has three parts to it. The first part studies sensation seeking and the role it plays in trading activity. This analysis makes use of both males and females. The second part jointly focuses on sensation seeking and overconfidence as explanations for trading activity. Because our overconfidence score can only be computed for young and middle-aged males, it contains fewer observations. The third part analyzes performance after transaction costs, categorized by the investor's degree of sensation seeking and overconfidence.

A. Sensation Seeking Results

Earlier, we mentioned that our proxy for sensation seeking is the number of final convictions for speeding. Admittedly, speeding convictions are not a perfect instrument for speeding because not all violators are caught. However, in Finland, where many fines are tied to income, there is less reason to believe that the motivation for traffic violations is a rational calculation based on the cost of one's time. For example, Jussi Salonoja, a wealthy businessman, received a 170,000 euro fine for driving 80km/hour in a 40km/hour zone, while Anssi Vanjoki, a Nokia executive, received an 80,000 euro ticket for driving 75km/hr in a 50km/hr zone.[18] Moreover, because of the extreme cost of being caught, compliance with traffic laws is likely to be greater in Finland than in the United States and most parts of Europe. Speeding convictions are not a signal that one is simply the unlucky driver who is almost randomly "fished out" from a sea of violators.

Table II reports regressions that explain three different measures of trading as a function of this measure of sensation seeking and a host of control variables. The first column, which uses probit estimation to study the decision of whether to trade or not, employs all investors in the sample. The second column employs investors who trade at least once and uses the natural logarithm of the number of trades over the sample period as the dependent variable.[19] Because this sample is censored to exclude those who do not trade, we use Heckman's two stage procedure to estimate the coefficients. The first stage obtains a Mill's ratio from the probit regression in the first column. The second stage, estimated with ordinary least squares, adds Mill's ratio as an additional regressor to obtain consistent estimates on the remaining variables. The third column uses the log of the Barber and Odean (2000, 2001) measure of turnover as the dependent variable.[20] The coefficients in this column are estimated with ordinary least squares.[21] The rightmost three columns report the corresponding *t*-statistics for the coefficients. All *t*-statistics and standard errors in the paper are robust, in that they are computed using White's heteroskedasticity-consistent standard error estimation procedure.[22]

The regressors for Table II include the number of ticket convictions as a predictor of trading activity. As can be seen from the bottom row, this measure of sensation seeking has coefficients that are highly significant for all of the measures of trading activity. The first column indicates that the *z*-score increases by .047 for each additional speeding ticket. For a propensity to trade of 0.5, (which is approximately the unconditional probability of trading), each additional ticket generates approximately a 2% increase in the probability of trading.[23] The second column indicates that the number of trades increases by a factor of 10% (that is, multiplies the base number of trades by a factor of exp(.098)) for each additional speeding ticket. The third column implies that each additional speeding ticket tends to increase turnover by about 11% (that is, multiplies base turnover by a factor of exp(0.101)). These effects control for age dummies and dummies for the number of stocks held in addition to the controls reported in Table II.[24]

The speeding ticket coefficients for the second and third columns in Table II are similar when we run the regressions separately for males and for females, and are 50-100% larger for car owners than for non-car owners. For males, the speeding ticket coefficients for the number of trades and turnover regressions are .084, and .101, while for females, they are .092, and .085, respectively. The probit regression in the first column has a coefficient on the tickets variable of .033 for males and .067 for females. For car owners, (with coefficients nearly identical to those reported in Table II) all of the coefficients are highly significant. For non-car owners only, the coefficients for the three regression specifications have *t*-statistics of 1.96, 3.74, and 5.71, respectively.

We also obtain similar coefficients on the speeding tickets variable when we run the regressions in the first two columns separately for buys and sells. For example, the probit regression in the first column generates a coefficient of .045 (t = 5.75) when the buy dummy is the dependent variable and .053 (t = 6.78) when the sell dummy is the dependent variable. The fact that these are similar and that the regression with the buy dummy as the dependent variable is highly significant dispels the notion that Table II's results are driven by asset sales to finance high fines for speeding.

In Finland, there are two types of speeding tickets. Mild violations—typically less than 15 kilometers per hour over the speed limit—receive a flat fine and more severe violations receive a fine related to income. When the Table II regressions employ both the number of flat fine tickets and the number of income-related fines as proxies for sensation seeking, we obtain similar coefficients on both regressors. For example, each additional income-related fine increases the number of trades by a factor of 10.6% while each additional flat fine increases the number of trades by a factor of 9.7%. However, the t-statistic on the coefficient for the income-related fine, 9.00, is about three times larger than the t-statistic for the number of flat fines. 3.05. The most likely explanation for the flat fine's larger standard error is that flat fines are rare (constituting 15.6% of tickets); officers rarely choose to enforce the law for mild speeding violations. This standard error pattern, which gives a far larger confidence interval for the flat fine coefficient, occurs for the other specifications as well. Other things equal, the number of flat fines is positively and marginally significantly related to log of turnover (beta = .064, t = 1.96), but the number of income-related fines has a coefficient that is 70% larger (beta = .108, t = 9.60). For the trade dummy probit regression, flat fines have a slightly larger coefficient but a far smaller significance level (beta = .052, t = 2.07) than that for the number of income-related fines (beta = .046, t = 5.09).

Greater degrees of sensation seeking should also be associated with the severity of a speeder's typical driving violation. Fines for the more severe violations in Finland, known as "day fines," are assessed (approximately) as a number of half days of foregone income. The number of half days assessed, referred to as "days fined," is based on the severity of the infraction. The mean days fined, averaged only across day fine penalties earned by each driver who has earned at least one day fine, is another proxy for sensation seeking. It measures the average severity of an investor's speeding violations. It has a significantly positive coefficient when it replaces number of speeding tickets in the Table II specifications. Compared to speeding tickets in the same regression, mean days fined also is a more significant predictor of the decision to trade and the log of the number of trades when added as an additional regressor to Table II's specifications. In the regressions, each additional day fine (about a half day of salary as a measure of severity) amounts to 0.77% more trades. The standard deviation of the average number of day fines is 4.39. Thus, a one standard deviation increase in the average number of day fines increases the number of trades by roughly 3.4%. This is almost 60% larger than the effect of a one standard deviation increase in the number of speeding tickets (0.586 more tickets) when the number of speeding tickets is used in the same regression.

One also can conclude that Table II's results are not driven by liquidity shocks that jointly affect driving and trading behavior. The inclusion of four additional liquidity shock variables—a dummy for getting married, divorced, or becoming unemployed, and change in the number of dependents—lead to similar results while the shock variables are by and large insignificant.

The reported coefficients on the control variables from Table II's regression are interesting in their own right and sensible. Financial wealth, income, and whether one is employed in a finance-related profession are positively related to trading activity even after controlling for the number of stocks in the investor's portfolio. Also, being unemployed is positively related to trading activity. Possibly, independently wealthy individuals trade for their own account rather than work.[25]

The gender effect in Table II's regression—men trade more—is extremely strong, even more so for single or widowed men. Thus, our proxy for sensation seeking does not explain the relationship between gender and trading that has been documented in the literature.

B. Overconfidence, Sensation Seeking, and Trading Activity

Barber and Odean (2001) contend that the relationship between gender and trading activity is due to the greater overconfidence of men. We investigate this by controlling for gender (focusing only on males) and looking at how variation in a direct measure of overconfidence influences their trading activity. Our analysis also controls for number of speeding tickets, a sensation seeking proxy, to assess whether overconfidence has any marginal explanatory power for trading activity.

Overconfidence is derived from the FAF self-confidence scale, which is interpreted by the FAF as follows:

> *"A person with a high score believes in himself. He views himself at least as intelligent as others and believes he will manage in life, if necessary, even without the help from others. He does not feel nervous or anxious in social situations; he does not expect others' approval and is not afraid of others' possible critique. A person with a low score is uncertain of himself and he may hate himself and his outlook. He gives up easily when facing difficulties and can even blame others for his failures: 'he has been given too difficult tasks.' As a result of lack of self-confidence he feels himself unsure and anxious in social situations, and can therefore avoid particular individuals who are self-confident and view him critically."*

The self-confidence measure for an individual is transformed into an overconfidence measure, which is a residual from a regression that uses controls for competence from the FAF, FTA, and FCSD datasets.[26] Table III Panel A reports the coefficients and test statistics for this regression. The controls include the regressors from Table II (except for number of speeding tickets and the finance professional dummy) as well as the composite intellectual ability score from the FAF assessment, which measures verbal, mathematical, and logical ability. (Our results are virtually identical if we enter these dimensions of ability as separate scores in lieu of the composite score.) Table III Panel A indicates that individuals' self-confidence scores are somewhat prescient about their future life success. Those who have greater FAF ability scores, who later in life achieve greater income, marry, and hold down jobs, tend to be the most self confident.

There also is an age pattern to the assessment. As age dummies represent an age range of the subject in 1997, higher age dummies generally correspond to those who took the leadership assessment in the more distant past (and to a small extent, those who entered military service at a later age).[27] Those who took the leadership assessment most recently exhibit the greatest self-confidence. One can only speculate about the reasons for this. On the one hand, it may reflect generational differences and economic changes in Finland. The successful economic growth of Finland and the waning influence of the Soviet Union (and later Russia) may have produced ever growing confidence among army recruits. On the other hand, our sample is filtered for those who own at least one stock during the 2 ½ years that precede our sample period. This may select more confident subjects among the very young.

The residual from Panel A's regression is our measure of overconfidence. The idea behind this is that self-confidence, as measured by a scale from the Finnish Armed Forces leadership assessment, is a combination of competence and overconfidence. Panel A's regression controls for competence and the residual represents overconfidence.

The first two rows of Table III Panel B provide direct evidence on the joint impact of sensation seeking and overconfidence on trading activity. Sensation seeking is highly significant except when measuring whether someone trades or not. The number of trades and turnover are significantly related to sensation seeking, even after controlling for overconfidence and the other regressors listed in the table, as well as unreported dummies for birth year and number of stocks in the portfolio. The economic effect, where significant, seems meaningful. For example, the middle regression indicates that each additional speeding ticket generates approximately 7% more trades.

Overconfidence also is significantly related to trading (at the 5% level), except when logged turnover is the dependent variable. In the case of logged number of trades, a unit increase in overconfidence (a regression adjusted stanine) generates almost a 4% increase in trades. Turnover is a bit of a mystery here. Barber and Odean (2001) found that the turnover of males exceeded that of females and attributed that to the greater overconfidence of males. However, within the male sample that took the FAF assessment, the sensation seeking proxy appears to be better at explaining turnover than overconfidence.

Why is it that sensation seeking has little effect on the decision of whether to trade or not, but overconfidence has such a large effect? One possibility is that sensation seekers achieve stimulation with each trade; a single trade offers very little stimulus. However, this is more likely a sample-specific finding: Restricting the sample so that it excludes older citizens as well as women significantly weakens the predictive power of sensation seeking on the decision to trade. This occurs even without the addition of the overconfidence variable. It appears that women and older male investors who receive few speeding tickets do not trade.

The same cannot be said for the relatively younger and exclusively male group who are in the FAF data sample. Even though their turnover ratios and number of trades are low, these young males still trade on rare occasions.

One should also not read too much into comparisons between the overconfidence and sensation seeking coefficients. Both of our measures of these concepts are noisy, downwardly biasing estimates of their coefficients. Not all sensation seekers are caught speeding, nor is sensation seeking the only motivation for a speeding ticket. Similarly, overconfidence is ultimately derived from an assessment taken years before we observe trading. Even if this assessment was able to generate a perfect measure of overconfidence at the time it was taken, (which is unlikely), the measure becomes a noisy proxy for our purposes if overconfidence changes over time.[28] This gives us some assurance that our conclusions are conservative when we observe a significant effect. On the other hand, one should pause before drawing strong conclusions from the absence of a significant effect.

C. Overconfidence, Sensation Seeking, and Performance after Trading Costs

If inside information motivates trades and this information is somehow related to the sensation seeking or overconfidence attribute, the overconfident and sensation seeking investors might trade more than others for rational reasons. If this was the case, the trades of sensation seekers and overconfident individuals would exhibit superior performance. In the model of Kyle and Wang (1997), for example, overconfidence survives as an attribute, as the trades of these investors do not harm them. Here, we show the opposite. All classes of investors, including those most overconfident and those most prone to sensation seeking, exhibit negative portfolio performance. This is because transaction costs exceed any potential profit that might be earned. This negative performance holds for multiple holding periods.

To assess performance, we examine the executed price of each buy trade and sell trade for all investors in our sample. Table IV, using daily share price and return data, reports the average of the differences between the subsequent one-day, five-day, twenty-day, and sixty-day returns between each day's (value-weighted) portfolio of buys and portfolio of sells, formed from categories of investors grouped by their overconfidence and sensation seeking attributes. Because we know transaction prices, the reported performance numbers in Table IV include the intra-day return on the day of transaction. A five-day return thus contains a bit more than five full days of returns. Reported performance also is net of the lowest available commission rate, 8.42 euros + 0.15% of value, for each buy or sell transaction, making our numbers conservative. Indeed, such a low commission was not available before the year 2000, a period that constitutes a portion of our sample. The lowest possible commission costs can be computed quite accurately because we have the necessary details of each trade.

If the buy portfolios have the same risk as the sell portfolios, their differenced returns should have means of zero. This is the standard test we look at. However, just averaging each multi-day return, using daily data, generates a classic overlapping data problem. If factor exposures on the buy and sell side are consistently different, consecutive multi-day returns observed at daily frequencies are positively correlated; this contaminates standard test statistics. The problem has to be resolved before assessing whether the average of the buy minus sell return differences significantly differs from zero.

To better understand this overlap, consider the one-day and five-day returns of portfolios of buys and sells on June 13 and 14 of the year 2000. For the June 13th portfolios, execution took place sometime on June 13. The one-day returns of the June 13 buy and sell portfolios stretch from a variety of intraday points on June 13 to the close on June 14. At least a portion of the June 14 return difference from the June 13 trades overlaps with the intraday returns of the one-day portfolio formed from buys and sells executed on June 14. Similarly, the five-day returns of the June 13 portfolio stretch from the middle of June 13 to the close on June 20. On average, 4 ½ days of returns overlap with the five-day returns of the June 14 buys and sells. Hence, standard *t*-tests exaggerate significance here.

In lieu of a GLS procedure, such as Hansen and Hodrick (1980), to address the exaggerated significance, we employ a variation of the technique used in Jegadeesh and Titman (1993). The innovation we present has to do with assigning transaction costs and intra-day returns to these trades. To understand the mathematics of this procedure, it is useful to illustrate it with an example, which will be a 5-day return. For simplicity, initially ignore the intra-day return and the commission cost. We also will ignore compounding, which is negligible, so that, for example, we view a five-day return as the sum of the daily returns on the five days comprising it.

The Jegadeesh and Titman (1993) insight is immediately apparent. With daily observations, the full-day return from say Wednesday, June 14, 2001 (close on the 13th to close on the 14th) appears in a rolling average of five-day returns as if it is computed as the sum of five buy portfolio minus sell portfolio return differences, with initial transaction dates of June 7, 8, 9, 12, and 13. Thus (except for compounding), the time series of daily buy-sell return differences, from portfolios generated by the five most recent buy-sell portfolios, is identical to the average of a rolling series of five-day returns, formed from each day's buy-sell portfolios. The advantage to the former is that the average daily buy-sell returns, computed with the former method, are likely to be uncorrelated, due to market efficiency. The lack of serial correlation within the sequence of such daily observed return differences allows an ordinary *t*-test of significance: the ratio of the average to the standard error of the average. An analogous approach can be applied to other rolling multi-day horizons.[29]

Our innovation is that we account for intra-day returns and commission costs in the computation. This is a bit trickier than one might think. The June 13, 2001 intraday return difference from buys and sells on June 13 has to be added to the June 13 observed return difference for the *t*-test to remain legitimate. If the intra-day return difference was added to June 14, for example, the observed return differences on June 13 and 14, formed as described above, would no longer be uncorrelated. Commissions are less problematic but we simply subtract them from the observed buy or sell return on the same day. Recall that the commission cost is 8.42 euros + 0.15% of the transaction value. If the amount bought (or sold) by investors of a given category is V euros and the number of buy (sell) transactions is N, the buy (sell) return is reduced by 8.42N/V + 0.0015. Combining intra-day returns by adding them to the sum of the five buy returns (or sell returns), and adjusting the return for commissions in this manner implies the unit of performance from averaging the daily return difference sums is a 5-day abnormal return difference. Longer or shorter units apply analogously in the Table IV columns for 1-day, 20-day, and 60-day return differences.[30]

Table IV thus reports appropriate *t*-statistics for what effectively might be thought of as the 1-day, 5-day, 20-day, and 60-day differences in the returns of the buy portfolios and the sell portfolios of investors of a given category—grouped by sensation seeking or overconfidence. These differences measure abnormal performance per dollar invested, after transaction costs, of each group of investors. As can be seen, all of the forty differences are negative, about half significantly so at the 5% significance level.[31] One cannot conclude from this evidence that performance is the motivation for trading by these investor categories.

Does performance differ across portfolios with different sensation seeking and overconfidence characteristics? Hirshleifer and Luo (2001) suggest that the worst performance should come from the least and most overconfident investors. It is intriguing that for three of the four investment horizons in Table IV, this holds true. However, in addition to properly benchmarking the significance level for a multiple comparison,[32] there are issues with omitted variables: Someone who trades frequently or in larger trade sizes, or who is a finance professional, may have lower transaction costs per dollar of trade, yet end up with higher aggregate costs from trading. Prior drafts of this paper have also analyzed monthly returns (before transaction costs) of stocks bought and sold in the past by various groupings of investors and none of these were significant. Therefore, we are reluctant to draw inferences about relative ability from comparisons of numbers in Table IV.

III. Summary and Conclusion

This paper has shown that some portion of trading is driven by behavioral attributes. Those who are sensation seekers (as measured by the number of speeding tickets received) and those who exhibit more overconfidence (as measured by a psychological assessment of each male entering the armed forces) trade more. Although our measure of sensation seeking, which is derived from driving records, is correlated with gender, it does not account for gender differences in trading activity.

These findings beg for investigation of other arenas where the behavioral attributes studied here tend to operate. Uncovering links between these attributes and other predicted economic behavior would suggest that our findings are part of a larger picture in which certain behavioral attributes play a key role in microeconomic behavior. For example, if sensation seekers are those who live for the moment, and overconfident investors have irrationally optimistic beliefs about the value of their human capital or their health prospects, we might expect these investors to have lower demand for insurance products (including life and health insurance). Moreover, we might expect sensation seekers to have lower savings rates and greater need for commitment in their consumption/investment plans.

Our results on how trading is affected by these attributes stem from analysis of a dataset that has several advantages over those used to study related issues in behavioral finance in the past. It is fairly comprehensive in the subjects it covers, lacks response bias, and allows us to control for a number of other variables that might explain trading activity. As a consequence of these controls, as well as additional tests, we do not believe that our results on the relation between sensation seeking and trading activity are driven by investor differences in risk aversion. First, our trading activity regressions control for the degree of diversification in the investor's portfolio by employing dummy variables for the number of stocks held and additionally control for both income and wealth. Second, a proxy for an investor's risk aversion—the ratio of his equity wealth to his total portfolio wealth—appears to be unrelated to that investor's sensation seeking attribute. Therefore, it is not surprising that employing this risk aversion proxy (in unreported regressions) as an additional control variable in our trading activity regressions has little impact on the coefficients or test statistics for the sensation seeking variable.

We have tried to be exhaustive in assessing whether other alternative rational explanations, besides risk aversion, account for our findings. Examination of these alternatives goes beyond what is reported in the paper. For example, our sensation seeking findings might be due to an endogeneity bias arising from active traders locating in urban areas where speeding enforcement is high. However, when we run Table II's regression separately for urban, suburban, and rural locations of residence, we find that there is a significant relation between speeding tickets and trading activity in all areas, including the rural areas. Another possibility is that income is not properly controlled for with our decile proxies, but alternative income and wealth controls, including finer categorizations of income and wealth at the extreme tails, do not seem to affect our results.

To further assess the validity of the sensation seeking explanation, we analyzed a second plausible metric of sensation seeking: sports car ownership. Regressions (containing the usual set of controls) of trading activity on a dummy variable for whether one owns a sports car indicate that sports car ownership is significantly related to trading activity, albeit to a lesser degree than the number of speeding tickets.

Despite the surprisingly strong results here, it is important to emphasize that the degree of trading activity in financial markets remains an anomaly. We have not calibrated our findings to suggest that sensation seeking and overconfidence explain a large proportion of observed trading activity. Rather, what we have learned is that fairly stable behavioral traits explain some cross-sectional differences in trading activity. This adds to the evidence suggesting that rational motivations, like rebalancing, cannot explain the volume of trade, because some of that volume appears to be clearly driven by behavioral motivations. Whether better measurement of the behavioral motivations we have analyzed or whether some other behavioral motivation can explain most of the observed trading activity is an open question for future research.

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Table I
Variable Descriptions and Descriptive Statistics

Table I describes the variables used in this study and provides summary statistics on them. Panel A provides detailed descriptions of the variables used, date or interval of measurement, and the source for the data used to construct the variable. Panel B reports means, medians, standard deviations, and interquartile ranges for the variables used in the study. Panel C contains the histogram for the scores reported on the self-confidence measure. Panel D is the correlation matrix for key variables used in the study. The sample is restricted to drivers in the province of Uusimaa or East Uusimaa who got their AB or B license before July 1, 1997, who owned stocks between January 1, 1995 and June 30, 1997, and for whom there is tax data from 1998. For the first two columns of Panel C and for the self-confidence correlation in Panel D, the sample is further restricted to males who took the FAF leadership inventory between January 1, 1982 and December 31, 2001. To assess the representativeness of the sample of drivers and 1995-97 stockholders whose overconfidence we study, the last two columns of Panel C report on the stanine distribution and reliability rates for all subjects who took the leadership inventory assessment.

Panel A. Variable Description

Variable	Data source	Measuring time	More details
Age	FTA + FCSD	Measured at 1997	Determined based on social security code
Male	FTA + FCSD	Does not change	Determined based on social security code
Married	FTA / Pop. Register	End 1998	
Cohabitor	FTA / Pop. Register	End 1998	
Unemployed	FTA	Year 1999	Drew unemployment benefits for at least one day in 1999
Homeowner	FTA	End 1998	Declared either real estate or apartment wealth at end 1998
Finance professional	FTA	End 1998	Empoyment in finance-related profession in 1998[1]
Total income	FTA	Year 1998	Declared total ordinary income + total capital income from 1998
Value of stock portfolio	FCSD	6/30/1997	Market value of stock portfolio
# stocks in portfolio	FCSD	6/30/1997	Number of different stock exchange listed stocks
# stock trades	FCSD	7/1/1997-11/29/2002	Number of open market trades of stocks
Portfolio turnover	FCSD	7/1/1997-11/29/2002	Computed as in Barber and Odean (2001) for stocks
# of speeding tickets	FVA	7/1/1997–12/31/2001	Total number of speeding tickets
Self confidence	FAF	When test taken	Psychological test self-confidence scores. The test scores are (approximately) stanine scores and vary between 1 (lowest) and 9 (highest). 0 denotes an unreliable score.
Ability score	FAF	When test taken	Psychological test ability scores. Each test score combines results from three separate tests that measure mathematical ability, verbal ability, and logical reasoning. The test scores are (approximately) stanine scores.

Explanations of abbreviations: FTA = Finnish Tax Administration; FCSD = Finnish Central Securities Depositary; FTA / Pop. Register = Tax authorities have obtained the information from the Finnish Population Register; FVA = Finnish Vehicle Administration; FAF = Finnish Armed Forces

[1] Represents one of the following professions (# in the sample): Portfolio manager or professional investor (117), dealer (FX and money market, 47), bank manager (mostly commercial banking, manager of branch, 297), stockbroker (61), stockbroker or portfolio manager assistant (29), investment advisor (generally low level, in bank branches, 20), miscellaneous investment baking or other higher level finance professional (68), financial manager (corporation, 45), equity analyst (33), miscellaneous low level investment banking related job (33), loan officer (commercial banking, 138), retired bank manager (23), CFO (227), analyst (may be other than equity analyst, 104). The tax authorities do not update the profession information often, as there was very little change in the profession data between 1998 and 2000.

Panel B. Means, Medians, Standard Deviations, and Interquartile Ranges of Variables

	Mean	Std. Deviation	Percentiles			N
			25	50	75	
Total income, EUR	35,559	73,337	14,888	25,474	40,425	95,804
Portfolio value, EUR	24,620	289,019	221	1,571	7,844	95,804
# stocks	2.050	2.546	1	1	2	95,804
# stock trades	14.67	119.40	0	1	6	95,804
Monthly portfolio turnover	0.019	0.056	0	0.002	0.014	90,467
Age	44.40	14.39	32	46	54	95,804
# speeding tickets	0.200	0.586	0	0	0	95,804
Ability score	6.425	1.749	5	6	8	12,466
Fraction of sample individuals						
Traded stocks	0.557	0.497	0	1	1	95,804
Male	0.471	0.499	0	0	1	95,804
Married	0.584	0.493	0	1	1	95,804
Cohabitor	0.024	0.152	0	0	0	95,804
Unemployed	0.060	0.237	0	0	0	95,515
Homeowner	0.759	0.427	1	1	1	95,804
Finance professional	0.014	0.116	0	0	0	91,129

Panel C. Distributions of the Self-confidence Measure (Males only)

	This sample		Full sample	
Stanine score	# observations	% of reliable scores	% of reliable scores	Stanine distribution
No reliable result	207			
1 (low self confidence)	135	1%	3%	4%
2	203	2%	5%	7%
3	432	3%	9%	12%
4	844	6%	14%	17%
5	1,941	15%	20%	20%
6	1,903	14%	14%	17%
7	2,961	23%	16%	12%
8	3,620	28%	15%	7%
9 (high self confidence)	1,114	8%	4%	4%
Totals	13,360	100%	100%	100%
Average		6.54	5.48	5.00

Panel D. Correlations between Key Variables

	Trade dummy	ln (#trades)	ln (Turnover)	Male	Age	# tickets	Self confidence
Trade dummy	1.000	N.A.	0.017	0.146	0.026	0.047	0.100
ln (#trades)		1.000	0.451	0.243	-0.007	0.095	0.058
ln (Turnover)			1.000	0.148	-0.204	0.101	0.022
Male				1.000	0.005	0.206	N.A.
Age					1.000	-0.108	-0.020
# tickets						1.000	0.012
Self confidence							1.000

Table II
Regressions of Trading Activity on Sensation Seeking and Control Variables

Table II reports coefficients and robust test statistics for a probit regression (column 1), a Heckman two-stage regression (column 2, which also reports the correlation coefficient between the residuals in the two stages), and an OLS regression (column 3). These regressions explain three measures of trading activity as a function of the number of speeding tickets and a host of control variables. Income and other socioeconomic data are from 1998. Unreported are coefficients on a set of dummies for the number of stocks in the investor's portfolio and birth year dummies. The sample is restricted to drivers in the province of Uusimaa or East Uusimaa who got their AB or B license before July 1, 1997, who owned stocks between January 1, 1995 and June 30, 1997, and for whom there is tax data from 1998.

	Coefficient			*t*-value		
	Dependent variable			Dependent variable		
Independent variables	Trade dummy	ln (#trades)	ln (Turnover)	Trade dummy	ln (#trades)	ln (Turnover)
# speeding tickets	0.047	0.098	0.101	5.75	9.68	9.98
Total income dummies						
Lowest	-0.133	-0.105	-0.081	-6.21	-3.30	-2.48
2	-0.039	-0.047	0.019	-1.90	-1.60	0.61
3	-0.030	-0.077	0.009	-1.52	-2.72	0.29
4	-0.031	-0.021	0.004	-1.58	-0.75	0.12
6	0.072	0.128	0.019	3.74	4.69	0.66
7	0.093	0.201	0.005	4.74	7.34	0.17
8	0.127	0.301	0.063	6.40	10.79	2.20
9	0.200	0.454	0.079	9.75	15.41	2.75
Highest	0.394	0.863	0.422	17.60	25.28	14.53
Financial wealth dummies						
Lowest	-0.994	-0.740	-0.193	-48.96	-8.67	-5.90
2	-0.788	-0.735	-0.177	-42.38	-10.90	-6.21
3	-0.504	-0.645	-0.048	-28.91	-14.37	-1.88
4	-0.335	-0.526	0.090	-19.27	-15.56	3.71
6	-0.037	-0.168	-0.008	-2.16	-7.91	-0.36
7	0.064	0.041	0.004	3.67	2.01	0.20
8	0.193	0.240	-0.199	4.84	7.70	-5.32
Highest	0.361	0.406	-0.106	12.85	13.05	-3.51
Other dummies						
Male	0.347	0.762	0.503	23.08	25.45	23.63
Married	0.029	0.062	0.164	2.19	3.41	8.48
Cohabitor	-0.070	-0.034	0.093	-1.79	-0.57	1.53
Male * married	-0.107	-0.351	-0.245	-5.55	-13.49	-9.10
Male * cohabitor	0.022	-0.082	-0.106	0.37	-1.03	-1.31
Unemployed	0.083	0.166	0.215	4.28	6.11	7.16
Homeowner	0.111	0.094	-0.100	8.84	4.99	-5.34
Finance professional	0.539	0.426	0.358	12.11	8.37	8.06
(Constant)	-0.325	0.603	-4.204	-5.32	4.45	-47.45
Inverse Mill's ratio		0.476			3.88	
ρ		0.358				
Pseudo R^2	0.153					
R^2		0.236	0.180			
Number of observations	90,868	50,713	50,224			

Table III
Regressions of Trading Activity on both Sensation Seeking and Overconfidence

Table III reports coefficients and robust test statistics for regressions. Panel A's cross-sectional regression uses ordered probit to estimate competence as the predicted value from a regression of self-confidence (from the FAF leadership assessment) on control variables that measure success in later life. Overconfidence is the residual from the regression. Panel B's probit, 2-stage Heckman (which also reports the correlation between the residuals of the two stages), and OLS regressions explain three measures of trading activity as a function of overconfidence, the number of speeding convictions, and a host of control variables. Income and other socioeconomic data are from 1998. Unreported in Panel B are coefficients on a set of dummies for the number of stocks in the investor's portfolio and birth year dummies. The sample is restricted to male drivers in the province of Uusimaa or East Uusimaa who got their AB or B license before July 1, 1997, who owned stocks between January 1, 1995 and June 30, 1997, and for whom there is tax data from 1998.

Panel A. Parsing out Competence from Self-confidence to Derive Overconfidence

Independent variables	Coefficient	*t*-value
Total income dummies		
Lowest	-0.031	-0.75
2	0.027	0.63
3	-0.061	-1.35
4	-0.128	-2.74
6	0.013	0.29
7	0.102	2.30
8	0.181	4.08
9	0.268	5.70
Highest	0.367	6.75
Portfolio value dummies		
Lowest	-0.032	-1.10
2	-0.080	-2.25
3	-0.020	-0.56
4	0.002	0.05
6	0.014	0.36
7	0.033	0.85
8	-0.004	-0.05
Highest	-0.020	-0.32
Other dummies		
Married	0.156	6.37
Cohabitor	-0.117	-2.17
Unemployed	-0.238	-4.85
Homeowner	0.009	0.43
Ability score	0.119	20.82
Age dummies		
23-29	0.420	5.59
30-34	0.358	4.97
35-39	0.129	1.82
40-44	-0.012	-0.16
Pseudo R^2	0.021	
Number of observations	12,379	

Panel B. Sensation Seeking, Overconfidence, and Trading Activity

	Coefficient			*t*-value		
	Dependent variable			Dependent variable		
Independent variables	Trade dummy	ln (#trades)	ln (Turnover)	Trade dummy	ln (#trades)	ln (Turnover)
# speeding tickets	-0.001	0.070	0.090	-0.05	3.48	4.82
Overconfidence	0.037	0.037	0.013	4.81	2.93	1.28
Total income dummies						
Lowest	-0.023	-0.203	-0.209	-0.40	-2.37	-2.64
2	0.075	0.051	-0.030	1.30	0.59	-0.38
3	0.135	-0.015	-0.006	2.25	-0.17	-0.07
4	0.029	-0.122	0.043	0.48	-1.31	0.52
6	0.267	0.303	0.133	4.47	3.13	1.66
7	0.307	0.386	0.127	5.22	3.95	1.66
8	0.493	0.679	0.272	7.96	5.97	3.57
9	0.564	0.777	0.237	8.63	6.37	2.93
Highest	0.868	1.293	0.665	10.36	8.65	7.52
Financial wealth dummies						
Lowest	-1.142	-1.010	-0.290	-21.39	-4.37	-4.33
2	-0.892	-0.923	-0.278	-16.91	-5.25	-4.33
3	-0.522	-0.812	-0.231	-9.88	-7.39	-3.82
4	-0.321	-0.588	-0.021	-5.87	-6.99	-0.36
6	0.023	-0.067	0.029	0.39	-1.01	0.47
7	0.206	0.157	0.127	3.20	2.20	2.05
8	0.275	0.317	-0.111	1.40	2.32	-0.77
Highest	0.362	0.346	-0.219	2.95	3.17	-2.10
Other dummies						
Married	-0.092	-0.324	-0.039	-2.74	-6.94	-1.00
Cohabitor	-0.134	-0.183	0.033	-1.80	-1.78	0.39
Unemployed	-0.072	0.050	0.257	-1.12	0.50	2.81
Homeowner	0.144	0.134	-0.016	4.77	2.86	-0.45
Finance professional	0.692	0.577	0.448	6.47	4.60	5.43
(Constant)	-0.639	1.502	-3.460	-1.67	2.17	-4.74
Inverse Mill's ratio		0.816			2.45	
ρ		0.532				
Pseudo R^2	0.156					
Adjusted R^2		0.154	0.178			
Number of observations	11,521	7,359	7,271			

Table IV
Performance after Transaction Costs for Investors Categorized by Sensation Seeking and Overconfidence

For holding periods of 1, 5, 20, and 60 days, Table IV reports the average difference between the returns of a daily sequence of buy portfolios and sell portfolios, formed from the buys and sells of a group of investors, after transaction costs. Each T-day holding period return is approximated as a sum of T 1-day returns formed with the procedure of Jegadeesh and Titman (1993) to get around the overlapping horizon problem. The table also reports *t*-statistics for the associated returns. These are based on Newey-West standard errors for 13 cases where the first-order autocorrelation coefficient is significant at the 5% level. The transaction cost of each trade, be it a buy or a sell, is assumed to be 8.42 euros + 0.15% · (the value of the trade). Groupings of investors are based on the number of speeding tickets (Panel A) and the investor's overconfidence quintile (Panel B). Days with no buys or no sells are eliminated from all computations.

Panel A. Performance by Number of Speeding Tickets

	Performance evaluation period							
	1 day		5 days		20 days		60 days	
# speeding tickets	Mean	*t*-value	Mean	*t*-value	Mean	*t*-value	Mean	*t*-value
0	-0.53%	-13.22	-0.27%	-2.66	-0.57%	-2.04	-0.68%	-0.93
1	-0.42%	-9.68	-0.27%	-2.97	-0.41%	-1.84	-0.47%	-0.84
2	-0.29%	-5.20	-0.15%	-1.48	-0.14%	-0.69	-0.50%	-1.13
3	-0.64%	-5.79	-0.26%	-1.19	-0.43%	-0.98	-0.65%	-0.75
>3	-0.51%	-4.27	-0.36%	-1.91	-0.13%	-0.34	-0.45%	-0.61

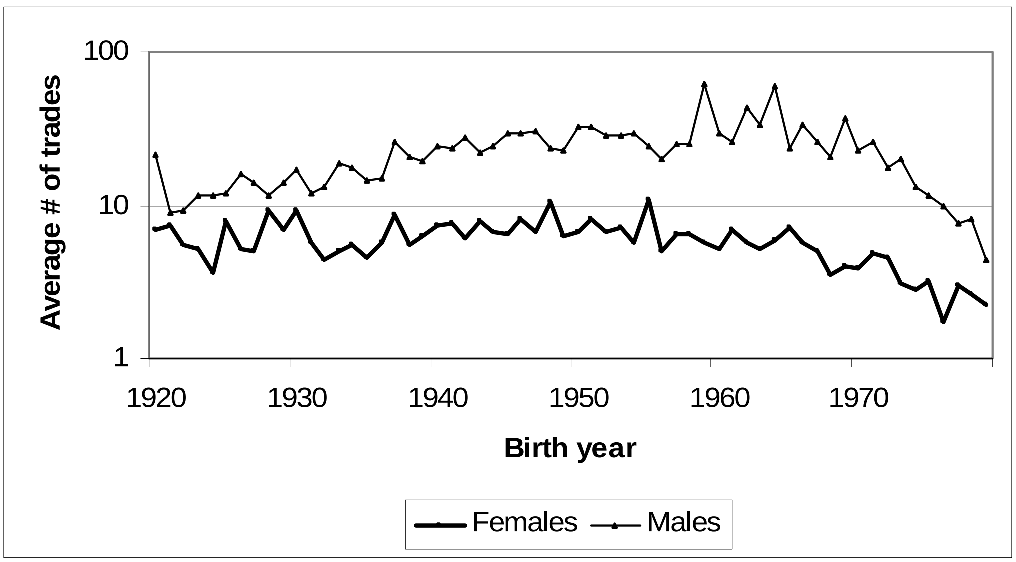
Panel B. Performance by Overconfidence Quintile

	Performance evaluation period							
Overconfidence	1 day		5 days		20 days		60 days	
quintile	Mean	*t*-value	Mean	*t*-value	Mean	*t*-value	Mean	*t*-value
Lowest	-0.66%	-9.85	-0.56%	-4.10	-1.08%	-3.44	-1.89%	-2.60
2	-0.62%	-7.75	-0.44%	-2.98	-0.62%	-2.04	-1.16%	-1.74
3	-0.43%	-6.60	-0.18%	-1.39	-0.14%	-0.49	-0.98%	-1.40
4	-0.44%	-6.07	-0.22%	-1.62	-0.43%	-1.31	-0.56%	-0.76
Highest	-0.74%	-10.03	-0.58%	-3.80	-0.61%	-1.76	-0.81%	-1.08

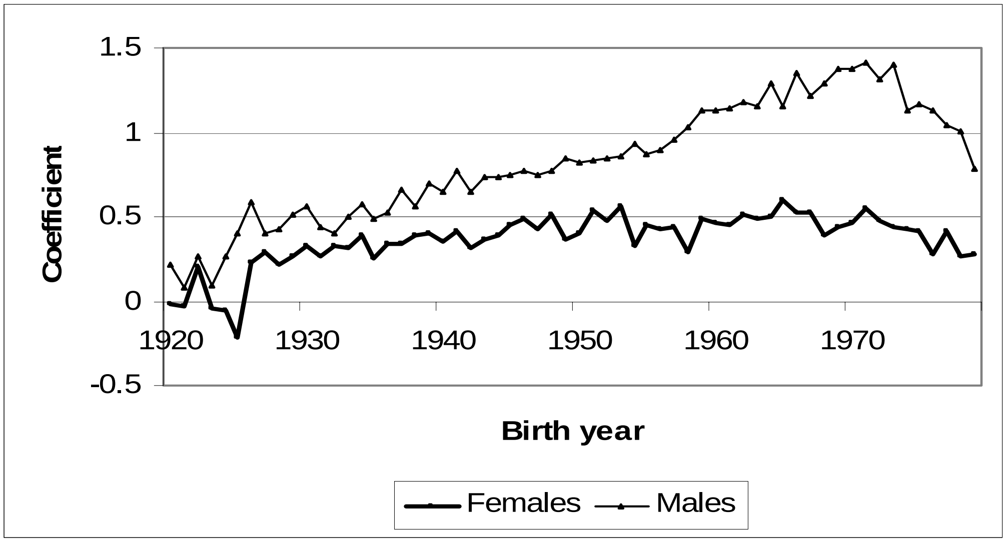
Figure 1
The joint effect of age and gender on trading activity and sensation seeking

Figure 1 plots trades and speeding tickets as a function of age and gender. Panel A plots number of trades from 7/1/1997-11/29/2002. Panel B effectively plots number of trades over the same period, controlling for income, wealth, and number of stocks in the portfolio. It reports coefficients from a regression of number of trades on birth year dummies (Females line) as well as the sum of the former coefficients and the product of birth year dummies and a male gender dummy (Males line). Regressors for income deciles, wealth deciles, and number of stocks are also controlled for. Panel C plots the number of speeding tickets from 7/1/1997-12/31/2001. The sample is restricted to drivers in the province of Uusimaa or East Uusimaa who got their AB or B license before July 1, 1997, who owned stocks between January 1, 1995 and June 30, 1997, and for whom there is tax data from 1998.

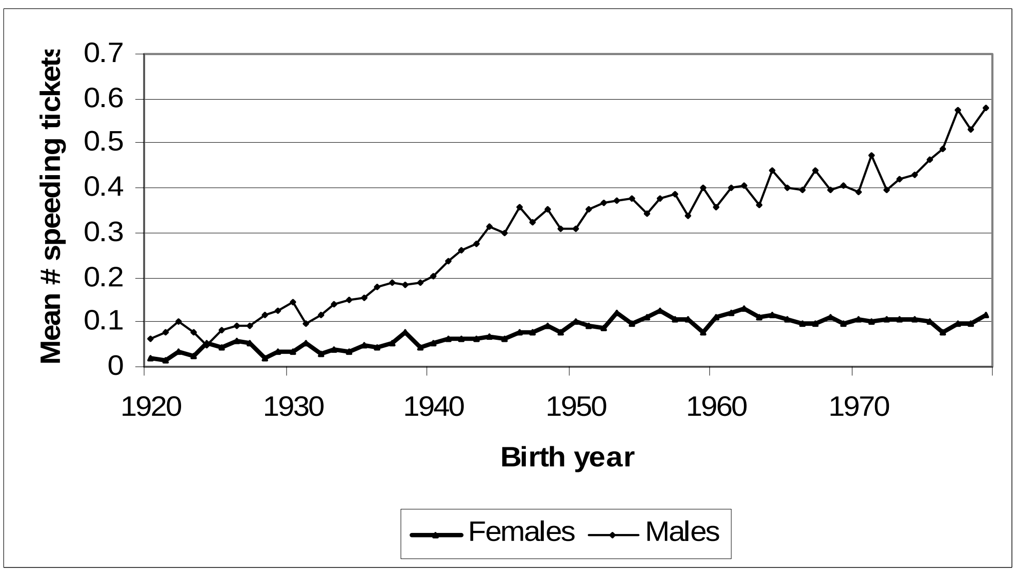
Panel A. Average Number of Trades as a Function of Gender and Birth Year



Panel B. Marginal Effects of Gender and Birth Year on Average Number of Trades with Effects of Control Variables Taken out



Panel C. Speeding Convictions as a Function of Gender and Birth Year



ENDNOTES

[1] Shefrin and Statman (1985), Ferris, Haugen, Makhija (1988), Odean (1999), Grinblatt and Keloharju (2001), and Grinblatt and Han (2005) argue that trading can arise as a consequence of a disposition effect. Graham, Harvey, and Huang (2005) contend that competence drives trading. There also is a large literature on overconfidence and trading, which we discuss later.

[2] See Zuckerman (1994), a key founder of the concept, for an excellent summary of this literature.

[3] For a review of the sensation seeking literature on gambling, see Raylu and Oei (2002). They document that active gambling games, like craps or poker, are more attractive to a sensation seeker than passive games with repeated small bets, like slot machines. Kumar (2006) concludes that investor-types with characteristics associated with an attraction to gambling prefer lottery-like stocks.

[4] Horvath and Zuckerman (1993) find that sensation seeking is significantly positively related to risky behavior in the following four areas of risk: criminal, minor rule violations (such as traffic offenses), financial (including gambling), and sports risks. Nicholson et al. (2005) find that safety risks (e.g., fast driving and cycling without a helmet) is significantly positively related to recreational, health, career, finance, and social risks. Salminen and Heiskanen (1997) show that traffic accidents are significantly correlated with home, work-related, and sports accidents.

[5] Dickerson (1984) discusses how the repetition of stimuli in gambling settings delights the sensation seeker. In roulette for example, he notes the stimulation from the spinning of the wheel, the croupier's calls, and the placing of bets.

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[6] There is, however, empirical evidence tying risk aversion to trading. Dorn and Huberman (2005) use survey data to document that a sample of German investors who self-report that stock investing is a low risk endeavor churn their portfolios. The survey asks questions of investors after experiencing five years of trades.

[7] Kyle and Wang's (1997) model has overconfidence as a commitment device for trading intensity. Odean (1998) and Benos (1998) develop a model in which overconfidence leads to trading. Daniel, Hirshleifer, and Subrahmanyam (1998) show that overconfident investors overweight private signals. Gervais and Odean (2001) show that investors whose overconfidence is a function of experience trade more in response to a given signal than less confident investors. Odean (1999) suggests that overconfidence may be responsible for some portion of trading. Barber and Odean (2001) test whether overconfidence drives trading using gender as a proxy for overconfidence. Glaser and Weber (2007), using data on 215 online investors who responded to a survey, find that the better than average effect is related to trading frequency. Using experimental data, Deaves et al. (2004) observe that miscalibration based overconfidence is positively related to trading activity, while Biais et al. (2005) find that miscalibration-based overconfidence reduces trading performance.

[8] As just one hypothetical example, assume that positive past performance generates lower self-assessed risk aversion among both passive and active investors. Further assume that (in contrast to passive investors) those who traded a lot and did poorly do not answer the survey (with embarrassment as the explanation). In this case, it seems plausible that one might spuriously infer a positive correlation between past churning and self-assessed aversion to risk from a survey.

[9] The questions also clearly differ from the types of questions offered in tests of optimism, like the LOT-R test. The use of "confidence" for skill-related outcomes and

"optimism" for exogenous outcomes is common. See Feather and Simon (1971), Hey (1984), Langer (1975), and Milburn (1978).

[10] See, for example, Barber and Odean (2001) and Agnew et al. (2003).

[11] High self monitors are more aware of how their behavior influences others. They also tend to be more aware of strategic behavior on the part of others.

[12] See, for example, Zuckerman, Eysenck, and Eysenck (1978) and Ball, Farnhill, and Wangeman (1984).

[13] See Begg and Langley (2001).

[14] The literature offers differing views on whether males actually are more miscalibrated than women. Lundeberg, Punćochaŕ, and Fox (1994) and Pulford and Colman (1996) argue that men are less well calibrated than women, particularly for tasks that are perceived to be in the masculine domain, whereas Beyer and Bowden (1997) and Beyer (1998) find women to be better calibrated. Lichtenstein and Fishhoff (1981), Lundeberg et al. (2000), Deaves et al. (2004), and Biais et al. (2005) find no difference in miscalibration between men and women.

[15] Non speeding offenses are fewer in number, varied across many categories, and difficult to interpret. For example, tickets do get issued for driving too slowly on a freeway. For these reasons, we focus only on speeding offenses in the sample. When we pool speeding with all other driving offenses as our measure of sensation seeking, we obtain highly similar results.

[16] Car owners are individuals who had a car registered in their name as of June 10, 2002. (Ownership of a truck, bus, or a related commercial vehicle is not considered in the analysis.) The mean number of tickets is lower for non-owners, as they tend to drive less than

owners. Many Finnish families have just one car, which usually is registered in the name of the spouse who uses the vehicle more (typically, the male).

[17] The correlations of the variables in the table with overconfidence, which is derived from self-confidence with a procedure described later, are similar to their correlations with self-confidence.

[18] Source: "Finn's speed fine is a bit rich," BBC News, February 10 2004. Mr. Vanjoki's fine was later reduced by 95% due to a drop in his executive stock option income.

[19] We also used Poisson estimation to obtain coefficients for a regression with the number of trades (rather than the log of trades) as the dependent variable. The *t*-statistic on the speeding conviction coefficient was 5.48.

[20] This is the average of buy turnover plus sell turnover. Buy turnover for a given month is the investor's portfolio weighted average of the ratio of shares bought of a stock to shares owned in the stock at the end of the month (or one if the ratio exceeds one). Sell turnover is the investor's portfolio weighted average of the ratio of shares sold of a stock to shares owned in the stock at the beginning of the month (or one if the ratio exceeds one). We average monthly buy turnover and sell turnover over all months to obtain an investor's overall buy turnover and sell turnover ratios. Months for which there is no end of month holding (for buy turnover) or beginning of month holding (for sell turnover) are excluded from the average. The number of observations for this measure of trading activity is slightly smaller than the sample for number of trades because of the absence of computable portfolio holdings.

Although not reported formally, adjusting our turnover measure in each month by subtracting the average turnover across all investors for that month, before averaging across months, yields approximately the same results as we report here. This robustness applies, irrespective of whether the subtracted average for the month equally weights all investors or weights them in proportion to their portfolio value.

[21] As in the log trades specification, we analyzed turnover with the Heckman two-stage procedure to account for self selection in the trading decision. The inverse Mill's ratio does not significantly differ from zero, so we only report the results from the more parsimonious OLS specification for observations with strictly positive turnover. The reported results are very similar to the results from the Heckman estimation.

[22] We obtain highly similar results when we run a Heckman regression using the log of the number of different stocks traded in lieu of the log of number of trades as the LHS-variable (*t*-value 8.11). The speeding ticket variable is also highly significant if we use the log of the ratio between the number of trades and the number of different stocks traded as the LHS variable (*t*-value = 7.41). Thus, doubling or halving your position in a stock also appears to be stimulating to sensation seekers.

[23] If a propensity to trade of 0.5 corresponds to a *z*-score of zero, the coefficient's .047 increase in the *z*-score per ticket has the cumulative normal probability moving from 0.5 (z=0) to approximately 0.52 (z=.047).

[24] The coefficients for a turnover regression specification that employs dummies for one speeding ticket, two speeding tickets, and three or more speeding tickets are .111, .209, and .367, respectively. Because so few subjects have four or more tickets, these coefficients are consistent with the reported regression in Table II, which has a .101 coefficient on number of speeding tickets. For the other two regressions as well, we obtain similar results to those reported in Table II when we employ dummies for tickets in lieu of number of speeding tickets. Significance in Table II also is not driven solely by the relatively infrequent trading among zero ticket investors. A regression analogous to that in Table II with one dummy for investors

that have at least one ticket and another for those that have at least two tickets has significant coefficients on both dummies. This indicates that having two tickets leads to significantly more trades than having one ticket.

[25] Depending on the specification, adding the product of unemployment and log of wealth as an additional control either makes the unemployment dummy significantly negative or insignificant. Also, we checked the robustness of our results by omitting finance professionals and unemployed investors from the sample. The results are virtually identical to those presented here.

[26] Our overconfidence measure is closely related to Larrick et al's (2007) overplacement measure, which is defined as the difference between a subject's perceived percentile in a test and the actual percentile she belongs to.

[27] Entrance to military service generally is from ages 18-20, but is never later than age 28.

[28] Daniel, Hirshleifer, and Subrahmanyam (1998), as well as Gervais and Odean (2001), suggest that overconfidence can change over time. This would bias us to finding no relationship between our overconfidence measure and trading activity.

[29] Because autocorrelated daily portfolio returns can be induced by microstructure considerations, like non-synchronous trading, we compute autocorrelation coefficients for the return difference series. Most of the first-order autocorrelations do not significantly differ from zero. We apply Newey-West standard errors to compute the *t*-statistics for those 13 holding period – portfolio combinations where the first-order autocorrelation coefficient differs significantly from zero at the 5% level. The adjustment has very little effect on our results and does not alter any of our conclusions.

[30] If a particular day lacks any buys or any sells for an investor category, we define it as a missing value for the summation of buy-sell portfolio differences for each return day it might apply to. This assignment arises from a desire to make each day's return difference sums approximate a market-neutral strategy. The reported numbers in Table IV best approximate the average of the overlapping multi-day return differences by dividing the sum of all daily return difference sums by the number of non-missing daily observations over the entire sample period for that category.

[31] The results are qualitatively similar for longer horizons as well.

[32] For example, it would be natural to test whether the performance of the extreme groups of investors (e.g., most vs. least overconfident) differ from each other. We find no significant differences between the performance of the extremes for any of the eight pairings in Table IV.