Sensation Seeking, Overconfidence, and Trading Activity

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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 are combined with data from an investor's tax filings, driving record, and psychological profile. We use the data 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.

JEL classification: G10, G11

1. Introduction

The extraordinarily high volume of equity trading that takes place on stock exchanges represents one of the greatest puzzles in finance.[1] The classic asset pricing models suggest that investors should optimally buy a single risky portfolio and hold it in perpetuity. Rebalancing motivations generate only negligible trading for most plausible return generating processes, even when the motive is a proper asset allocation between cash and risky assets.

Researchers have offered a variety of explanations for why trading volume is so large, but these are not fully satisfactory. The obvious candidate, heterogeneous information, does not immediately generate rational trading. Milgrom and Stokey (1982) argued that in the presence of common knowledge, there is no rational trade, even with heterogeneous information signals. Models with disagreement require noise trading to generate trading volume.[2] Without a satisfactory explanation of what drives the noise trading and a calibration that accounts for observed trading, trading volume remains a puzzle.

As a consequence of the failure of traditional models to explain trading, empiricists have begun to study and document how behavioral factors might explain trade. Odean (1999), Grinblatt and Keloharju (2001), and Grinblatt and Han (2005) argue that trading can arise as a consequence of a disposition effect. Odean (1998, 1999) suggests that overconfidence may drive excessive trading. Barber and Odean (2001) find that gender is related to trading—the portfolios of males exhibit greater turnover—and that this is due to their greater overconfidence. Gervais and Odean (2001) develop a model in which successful chance experiences can generate overconfidence and lead to excessive trading. Graham, Harvey, and Huang (2005) contend that competence drives trading.

[1] See, for example, Odean (1999) and Barber and Odean (2000, 2002).
[2] See Weiss (1979), Grossman and Stiglitz (1980), and Pfleiderer (1984).

This paper employs data on the psychological traits of each investor to show that trading may be driven by two emotional considerations: The first is sensation seeking, which is the search for novel, intense, and varied experiences generally associated with real or imagined physical, social, and financial risks; the second is overconfidence, which is the tendency to place an irrationally excessive degree of confidence in one's abilities and beliefs. Using a comprehensive dataset from Finland, which offers a remarkable number of control variables, we show that investors who are most prone to sensation seeking and those who are most overconfident trade the most. To our best knowledge, this is the first study to specifically focus on sensation seeking as a motivation for trade and the first that employs comprehensive data to directly measure overconfidence and study its relationship to trading.

A potential link between sensation seeking and trading activity should be apparent to anyone who has spent time in a casino. Gambling, which the psychology literature has tied to sensation seeking,[3] is a worldwide industry, generating over $2 trillion in revenues each year.[4] There also is widespread unreported and often illegal gambling activity that most everyone is acquainted with and which frequently is reported on in the popular press. Given the consumptive utility enjoyed in all sorts of activities where an element of risk and thrill is involved, it would truly be surprising if some consumers did not enjoy the thrill from trading in the stock market. A recent paper by Kumar (2005) concludes that investor-types with characteristics associated with an attraction to gambling prefer lottery-like stocks.

A link between overconfidence and trading activity is also plausible, as recent literature has noted.[5] When one's private valuation of a stock differs from that of the market,

[3] For a review of the literature, see Raylu and Oei (2002).

[4] Source: BBC News World Edition August 22, 2005 reporting on "Place Your Bets, Part 3."

[5] Barber and Odean (2001) test whether overconfidence drives trading using gender as a proxy for overconfidence. Glaser and Weber (2004), 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. (2003)

the overconfident investor places more validity on his private valuation and less on the market's valuation. This can occur for two related reasons. The first is hubris or what is sometimes referred to as the "better than average effect." The other is "miscalibration." This arises when the confidence interval around the investor's private signal is tighter than it is in reality. Both forms of overconfidence lead the overconfident investor to form posteriors with excessive weight on private signals. This generates larger trades than would be observed in a less confident investor.

We measure sensation seeking as the number of automobile speeding convictions earned by an investor over a multi-year period. Zuckerman (1994), one of the pioneers of the concept, 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.

We derive the overconfidence measure from a standard psychological test. This test is given to all Finnish males at approximately the age of 19 or 20 (generally, many years prior to observation of an investor's trading activity). One of the scales from the test measures self-confidence. As this confidence measure is a combination of talent and overconfidence, we use regression analysis to control for talent 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.

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observe that overconfidence is positively related to trading activity, while Biais et al (2005) find that overconfidence reduces trading performance.

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, there does not appear to be a relationship between overconfidence and turnover. In light of the Barber and Odean (2001) conclusion that turnover is related to overconfidence, this finding points to the importance of direct measurement of behavioral attributes.

The paper is organized as follows: Section 2 offers motivation for the paper and describes the data. Section 3 presents the results on sensation seeking, overconfidence, and trading activity. Section 4 concludes the paper.

2. 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.[6] 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 reports coefficients on dummies for birth year and the sum of those coefficients and those on the product of a male gender dummy and the same birth year dummies, controlling for income decile dummies and wealth decile dummies. The pattern is a bit different. Now, except for those who are under age 23 at the start of our stock trading sample period, the gap

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

between the trading inclinations of men and women seems to diminish with age. Still, males trade more than females, irrespective of age.

What lies behind the greater tendency of males to trade? One possibility is that males enjoy the thrill of trading to a greater extent than females. Barber and Odean (2001) argued that one factor that might explain gender-related differences in trading activity is that the entertainment value of trading has a consumptive appeal that is similar to the thrill obtained from gambling. In the psychology literature, the gambler's thrill derives from an attribute known as "sensation seeking." This literature has shown that this attribute varies across investors by age and gender. Ultimately, Barber and Odean (2001) dismissed entertainment as an explanation for their results in favor of gender-based differences in overconfidence. This is because trading volume, as measured by turnover, was largely invariant to the fraction of an investor's net worth invested in common stock.[7] We think this dismissal is premature. 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 is a marked similarity between the two graphs in Panels B and C.[8] Irrespective of whether sensation seeking ultimately accounts for the trading pattern in Panel B's graph, we find it difficult to wholly dismiss it as a motivation for trading activity when the evidence supporting this dismissal is so indirect. It would clearly be interesting to run a horse race between sensation seeking and overconfidence if one had direct measures of these attributes for each investor. We are fortunate to be able to analyze such data.

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[7] This argument hinges on the assumption that some fixed fraction of one's wealth must be invested prudently, even if entertainment from the act of trading drives much of observed trading activity.

[8] One has to be cautious about drawing conclusions from this similarity. As Ameriks and Zeldes (2004) and others point out, however, it is very difficult to disentangle cohort, age, and time effects from each other.

2.1 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. To the extent that markets are efficient, trading frequency has costly financial consequences, but these are not tied to the risk aversion parameter. 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, but it does not increase volatility *per se*.

There is reason to believe that males are more prone to sensation seeking behavior.[9] 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.[10] A review article by Jonah (1997) documents that sensation seeking is significantly related to risky driving.

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

[10] See Begg and Langley (2001).

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.

2.2 Overconfidence

The second explanation we investigate for the greater trading of males is overconfidence. The literature offers differing views on whether males actually are more overconfident than women. Lundeberg, Puncochar, and Fox (1994) argue that men are more overconfident than women, particularly for tasks that are perceived to be in the masculine domain. Pulford and Colman (1996) find that men are slightly more overconfident. However, Deaux and Farris (1977), Beyer (1997), and Beyer and Bowden (1998) find that men have higher self perceptions than women but also tend to be better—not less—calibrated. Lichtenstein and Fishhoff (1981), Lundeberg et al (2000), Deaves et al (2003), and Biais et al (2005) find no difference in overconfidence between men and women.

To assess whether 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 measures on a large sample of subjects from an extensive psychological profile of those subjects. Our data also offer the possibility of a much cleaner test of whether overconfidence causes excessive 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 overconfidence is a stable characteristic that influences economic behavior throughout one's lifetime. 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.

2.3 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 data set, 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.
- 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 professional 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.[11] We use this data to measure differences in the sensation seeking attribute across investors.
- 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 exam, which includes

[11] 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.

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). 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 the start of 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.

2.3 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 1 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 1, 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 exam. 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 relatively large correlation with various measures of a subject's trading activity, but self-confidence, described later, is close to being uncorrelated with the number of tickets earned.[12] 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.

3. Results

Our analysis has two 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.

[12] 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.

3.1 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.[13] 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 2 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.[14] 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 Barber and Odean (2000,

[13] 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.

[14] 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.

2001) measure of turnover as the dependent variable.[15] The coefficients in this column are estimated with ordinary least squares.[16] 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.

The regressors for Table 2 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 probability of trading increases by 4.7% for each additional speeding ticket. The second column indicates that the number of trades increases by 9.8% for each additional speeding ticket. Annualizing the coefficient in the third column (multiplying by 12) implies that each additional speeding ticket tends to increase turnover by about 3.6% per year. Starting from the annualized average turnover rate of about 40% per year among those who traded stocks (Table 1's monthly average of .019 times twelve, divided by the 56% who traded stocks), each additional ticket increases turnover by a factor of 1.09. These effects

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[15] 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.

[16] As in the log number of trades specification, we first use 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.

control for age dummies and dummies for the number of stocks held in addition to the controls reported in Table 2.[17]

The sensation seeking coefficients for the second and third columns in Table 2 are highly similar when we run the regressions separately for males and for females. For males, the coefficients on sensation seeking for the number of trades and turnover regressions are .084, and .003, while for females, they are .092, and .002, respectively. The probit regression in the first column has a coefficient on the tickets variable of .033 for males and .067 for females. All of these coefficients are highly significant.

We 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 2's results are driven by asset sales to finance high fines for speeding.

Another indication that cash needs do not drive the link between speeding tickets and trading activity comes from regressions based on the type of speeding ticket. In Finland, there are two types of speeding tickets. Mild violations receive a flat fine and more severe violations receive a fine related to income. When the Table 2 regressions employ the number of flat fine tickets as the proxy for sensation seeking, the coefficient is highly similar to the corresponding regressions in which the number of income-related speeding violations is the

[17] The coefficients for a turnover regression specification that employs dummies for one speeding ticket, two speeding tickets, and three or more speeding tickets are .003, .008, and .011, respectively. Because so few subjects have four or more tickets, these coefficients are consistent with the reported regression in Table 2, which has a .003 coefficient on number of speeding tickets. For the other two regressions as well, we obtain similar results to those reported in Table 2 when we employ dummies for tickets in lieu of number of speeding tickets.

proxy for sensation seeking. For example, each additional income-related fine increases the number of trades by 10.1% while each additional flat fine increases the number of trades by 9.7%.

Greater degrees of sensation seeking should not only be associated with greater numbers of both mild and severe speeding violations, they should also be associated with some of the more severe violations being even more severe. 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, has a significantly positive coefficient when it replaces number of speeding tickets in the Table 2 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 2's specifications.

The reported coefficients on the control variables 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. This may be a retiree effect; it may be that independently wealthy individuals trade for their own account rather than work; finally, it may simply reflect that those who lose their jobs have to liquidate their financial wealth to consume.

The gender effect in Table 2's regression—men trade more—is extremely strong, even more so for single or widowed men. Moreover, as can be seen in Figure 2, the relationship between age, gender, and trading remains about the same as in Figure 1, Panel B, even after controlling for all of the remaining non-gender related regressors in Table 2, including our sensation seeking proxy. This is to be expected even if the sensation seeking trait fully explains the relationship between age, gender, and trading activity. Speeding tickets represent an imperfect proxy for sensation seeking. As a consequence, other sensation seeking correlates, such as age and gender, would have marginal explanatory power for trading activity (or any other behavior that true sensation seeking generates).

3.2 Overconfidence, Sensation Seeking, and Trading Activity

Barber and Odean (2001) have argued 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 talent from the FAF, FTA, and FCSD datasets. Table 3 Panel A reports the coefficients and test statistics for this regression. The controls include the regressors from Table 2 (except for number of speeding tickets and the finance professional dummy) as well as the composite intellectual ability score from the FAF exam, 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 3 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 exam. As age dummies represent an age range of the subject in 1997, higher age dummies generally correspond to those who took the exam in the more distant past (and to a small extent, those who entered military service at a later age).[18] Those who took the exam 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

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

leadership assessment, is a combination of talent and overconfidence. Panel A's regression controls for talent and the residual represents overconfidence.

The last two rows of Table 3 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.

Overconfidence also is significantly related to trading (at the 5% level), except when turnover is the dependent variable. 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 exam, the sensation seeking proxy appears to be better at explaining turnover than overconfidence. Since we know that males are more prone to sensation seeking than females, it is possible that the Barber and Odean (2001) gender difference in turnover is driven more by the gender difference in the sensation seeking trait than by the gender difference in the overconfidence trait. One might also argue, as with any insignificant result, that the lack of a relationship between overconfidence and turnover is driven by error in measuring true overconfidence. However, if that were the case, it would be difficult to explain the other highly significant coefficients for overconfidence in the same table.

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.

4. Summary and Conclusion

This paper has shown that, for some investors, 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. The overconfidence proxy is more related to whether an investor trades at all. The sensation seeking proxy is more related to the turnover ratio. These findings are derived from 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 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 if the probability of getting a speeding ticket (but not the proclivity to speed) is tied to trading activity via a third factor. One such possibility is that active traders locate in urban areas where speeding enforcement is high. However, when we run Table 2'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. However, we have run the same regressions with finer categorizations of income at the extreme tails, as well as direct measures of income. Alternative income and wealth controls do not seem to affect our results. A third possibility is that inside information motivates trades and this information is somehow related to the sensation seeking or overconfidence attribute. However, if this was the case, the trades of sensation seekers and overconfident individuals would exhibit superior performance. There is no evidence of this in the data. The weekly and monthly returns of portfolios consisting of the past buys of investor-groups sorted by number of speeding tickets and overconfidence quintiles do not significantly differ from the returns of their corresponding sell portfolios. This absence of performance holds for multiple portfolio formation periods, ranging from the past week to the past year.

Of course, it is theoretically possible that market making or other shorter-term motives drive the volume difference between low and high sensation seekers and between the least and most overconfident investors. We doubt this is true, in part because we obtain strong results even when controlling for whether the investor works in a finance-related profession. However, further study of this alternative hypothesis, while beyond of the scope of this paper, might be an interesting topic for future research—particularly if it can be conducted with high frequency data.

It also seems difficult to defend against the argument that our measures of sensation seeking and overconfidence are better labeled by some other psychological attribute or some mix of other psychological attributes than the ones we highlight here. However, we doubt the science of labeling psychological concepts is so precise that sensation seeking and overconfidence would be totally orthogonal to the newly-labeled concepts. We started with our two concepts because they seemed plausible as explanations for trading and then tried to find ways of measuring them. For example, to further assess the validity of the sensation seeking explanation, we analyzed a second metric of sensation seeking that has been explored in the psychology literature: 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. In the end, however, it is not terribly important to defend the labeling of what we are measuring. If it turns out that speeding tickets and the FAF self-confidence measure capture other non-neoclassical traits, the key point of this paper is still valid: that psychological factors, outside the neoclassical realm, drive some component of trading activity.

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 cross-sectional 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 1
Variable descriptions and descriptive statistics
Table 1 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.

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)	Turnover	Male	Age	# tickets	Self confidence
Trade dummy	1.000	N.A.	0.278	0.146	0.026	0.047	0.100
ln(#trades)		1.000	0.252	0.243	-0.007	0.095	0.058
Turnover			1.000	0.113	-0.076	0.068	0.040
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 2
Regressions of trading activity on sensation seeking and control variables

Table 2 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)	Turnover	Trade dummy	ln (#trades)	Turnover
(Constant)	-0.325	0.603	0.0847	-5.32	4.45	23.29
Total income dummies						
Lowest	-0.133	-0.105	-0.0037	-6.21	-3.30	-2.21
2	-0.039	-0.047	-0.0012	-1.90	-1.60	-0.79
3	-0.030	-0.077	-0.0004	-1.52	-2.72	-0.23
4	-0.031	-0.021	0.0000	-1.58	-0.75	-0.03
6	0.072	0.128	-0.0004	3.74	4.69	-0.29
7	0.093	0.201	-0.0013	4.74	7.34	-0.89
8	0.127	0.301	-0.0001	6.40	10.79	-0.04
9	0.200	0.454	-0.0016	9.75	15.41	-1.17
Highest	0.394	0.863	0.0041	17.60	25.28	2.94
Financial wealth dummies						
Lowest	-0.994	-0.740	-0.0189	-48.96	-8.67	-15.04
2	-0.788	-0.735	-0.0149	-42.38	-10.90	-11.85
3	-0.504	-0.645	-0.0084	-28.91	-14.37	-6.68
4	-0.335	-0.526	-0.0013	-19.27	-15.56	-1.07
6	-0.037	-0.168	-0.0012	-2.16	-7.91	-1.20
7	0.064	0.041	0.0015	3.67	2.01	1.54
8	0.193	0.240	-0.0022	4.84	7.70	-2.11
Highest	0.361	0.406	0.0021	12.85	13.05	2.09
Other dummies						
Male	0.347	0.762	0.0147	23.08	25.45	14.53
Married	0.029	0.062	0.0038	2.19	3.41	4.56
Cohabitor	-0.070	-0.034	0.0016	-1.79	-0.57	0.49
Male * married	-0.107	-0.351	-0.0061	-5.55	-13.49	-4.67
Male * cohabitor	0.022	-0.082	-0.0054	0.37	-1.03	-1.21
Unemployed	0.083	0.166	0.0107	4.28	6.11	6.15
Homeowner	0.111	0.094	-0.0061	8.84	4.99	-5.83
Finance professional	0.539	0.426	0.0129	12.11	8.37	5.05
# speeding tickets	0.047	0.098	0.0032	5.75	9.68	5.39
Inverse Mill's ratio		0.476			3.88	
ρ		0.358				
Pseudo R^2	0.153					
R^2		0.236	0.094			
Number of observations	90,868	50,713	50,224			

Table 3

Regressions of trading activity on both sensation seeking and overconfidence

Table 3 reports coefficients and robust test statistics for regressions. Panel A's cross-sectional regression uses ordered probit to estimate talent 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 talent 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	

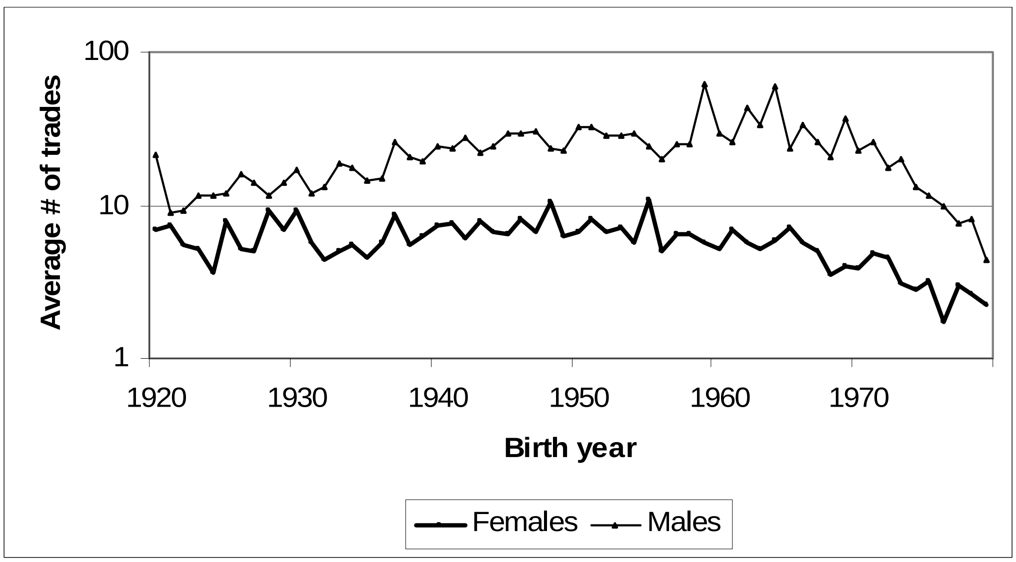
Panel B. Sensation seeking, overconfidence, and trading activity

	Coefficient			t-value		
	Dependent variable			Dependent variable		
Independent variables	Trade dummy	ln (#trades)	Turnover	Trade dummy	ln (#trades)	Turnover
(Constant)	-0.639	1.502	0.1025	-1.67	2.17	5.21
Total income dummies						
Lowest	-0.023	-0.203	-0.0077	-0.40	-2.37	-1.48
2	0.075	0.051	-0.0061	1.30	0.59	-1.25
3	0.135	-0.015	-0.0046	2.25	-0.17	-0.90
4	0.029	-0.122	-0.0013	0.48	-1.31	-0.24
6	0.267	0.303	0.0043	4.47	3.13	0.81
7	0.307	0.386	0.0031	5.22	3.95	0.59
8	0.493	0.679	0.0057	7.96	5.97	1.09
9	0.564	0.777	0.0025	8.63	6.37	0.51
Highest	0.868	1.293	0.0178	10.36	8.65	2.95
Financial wealth dummies						
Lowest	-1.142	-1.010	-0.0039	-21.39	-4.37	-1.12
2	-0.892	-0.923	-0.0164	-16.91	-5.25	-5.02
3	-0.522	-0.812	-0.0126	-9.88	-7.39	-3.86
4	-0.321	-0.588	-0.0044	-5.87	-6.99	-1.29
6	0.023	-0.067	0.0030	0.39	-1.01	0.91
7	0.206	0.157	0.0042	3.20	2.20	1.23
8	0.275	0.317	-0.0189	1.40	2.32	-3.31
Highest	0.362	0.346	-0.0097	2.95	3.17	-1.93
Other dummies						
Married	-0.092	-0.324	0.0011	-2.74	-6.94	0.39
Cohabitor	-0.134	-0.183	-0.0027	-1.80	-1.78	-0.48
Unemployed	-0.072	0.050	0.0219	-1.12	0.50	2.71
Homeowner	0.144	0.134	-0.0029	4.77	2.86	-1.21
Finance professional	0.692	0.577	0.0191	6.47	4.60	3.17
# speeding tickets	-0.001	0.070	0.0042	-0.05	3.48	3.24
Overconfidence	0.037	0.037	0.0004	4.81	2.93	0.61
Inverse Mill's ratio		0.816			2.45	
ρ		0.532				
Pseudo R^2	0.156					
Adjusted R^2		0.154	0.112			
Number of observations	11,521	7,359	7,271			

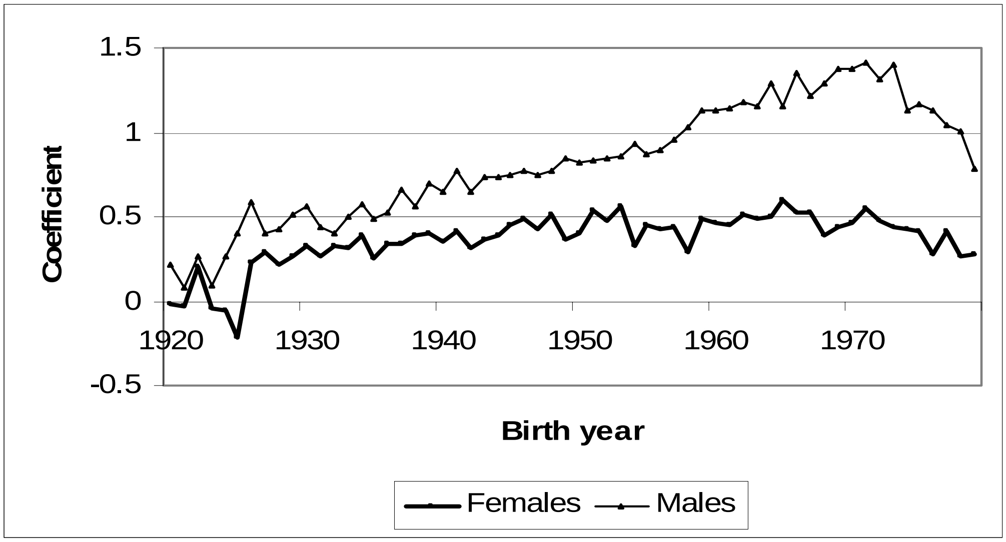
Figure 1
The joint effect of age and gender on trading activity and sensation seeking

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

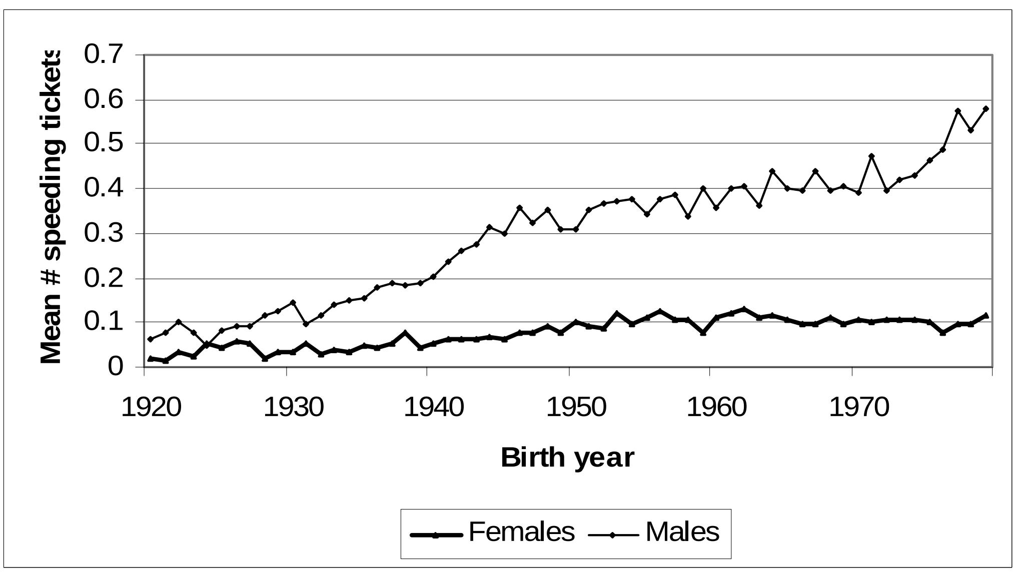


Figure 2
The joint effect of age and gender on trading activity controlling for sensation seeking

Figure 2 effectively plots the number of trades from 1997-2002 for males and females, averaged for each birth-year cohort controlling for the non-gender regressors in Table 2. It reports the coefficients on birth year dummies (Females line) and on the sum of the former coefficients and the product of age and a male gender dummy (Males line) are given in the graph. The trades are from 7/1/1997-11/29/2002 on the vertical axis. 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.