Leveraging Overconfidence

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Abstract

In theory, overconfident investors with a budget constraint use leverage more, trade more, and perform worse than well-calibrated investors. We confirm these predictions empirically by analyzing the overconfidence, trading, and performance of retail investors who use margin. Using survey data, we measure overconfidence as the difference between an investor's self-assessment of knowledge and tested knowledge; margin investors have greater overconfidence than cash investors. Using broker data, we find margin investors trade more, speculate more, and have worse security selection ability than cash investors. A long-short portfolio that follows the trades of margin investors loses 35 bps per day.

Can overconfidence lead investors to use leverage to their detriment? We examine this question theoretically and empirically. Our analysis begins with the development of a theoretical model based on Odean (1998) and Eyster, Rabin, and Vayanos (2019). High-skilled (e.g., professional) and low-skilled (e.g., retail) traders receive private signals about the terminal value of a risky asset in zero net supply; high-skilled traders receive a high precision signal, the low-skilled traders a low precision signal. Low-skilled traders may be overconfident in that they overestimate the precision of their private signal. Without regard to each other's signals, traders submit demand schedules and trade at the market clearing price. Leverage is modeled by assuming traders face exogenous budget constraints. In this model, three important predictions arise: low-skill investors who are overconfident are (1) more likely to use margin, (2) trade more actively, and (3) perform worse.

To test the empirical predictions of this model, we analyze the behavior and common stock trading of individual investors, comparing the behavior, trading habits, and performance of investors who use margin (i.e., use leverage) to those who don't. This is a particularly good setting to test our predictions as it is likely that the typical individual investor is at an information disadvantage to institutional investors when trading. Of course, some individuals are good traders and some institutions are bad traders. However, on average is it likely that individual investors have less skill and information than professional investors.

To test our first prediction, that overconfidence will lead investors to use margin, we use survey data from the National Financial Capability Study administered by the FINRA Investor Education Foundation. Specifically, we analyze responses of 1,601 respondents from the 2015 Investor Survey; 37% report having a margin account and 18% report having experience buying stock on margin. Survey respondents take two quizzes, a 10-question quiz that measures investment literacy and a 6-question quiz that measures financial literacy. Separately, respondents are asked to self-assess their investment knowledge and financial knowledge on a 7-point Likert scale. We measure overconfidence in investment knowledge as the difference in a respondent's percentile rank on self-assessed investment knowledge less the respondent's percentile rank on the investment quiz. There is an analogous calculation for overconfidence in financial knowledge.

As shown in Figure 1, investors who trade on margin (Panel C) have greater overconfidence than investors with margin accounts but no margin experience (Panel B) or investors with cash accounts (Panel A). For example, investors with experience trading on margin are at the 65^{th} percentile in their self-assessed financial knowledge, but the 37^{th} percentile on quizzed financial knowledge (Panel C, left pair of bars).

To test the robustness of this positive relationship between investor overconfidence and margin accounts, we estimate a linear probability model where the dependent variable is an indicator that equals one if the investor has a margin account. The key independent variable is measured overconfidence (based on either investment or financial knowledge). To this baseline regression we include a number of demographic controls (e.g., marital status, gender, age, etc.) and preference or trust variables (e.g., measures of risk tolerance, portfolio allocations, trust in financial markets). In the full model with all control variables, the probability of having a margin account is positively related to the overconfidence measures and the effects are economically large. A one standard deviation increase in investment overconfidence is associated with a 7.9 percentage point increase in the probability of having a margin account, which represents a 21% increase relative to the baseline probability of having a margin account in this sample (37%).[1] A one standard deviation increase in financial overconfidence has similar effects.

In additional tests, we analyze the use of margin conditional on having a margin account by analyzing the subsample of margin account holders. In these analyses, the dependent variable is an indicator that takes a value of one if the investor used margin to purchase stocks. The key independent variable is measured overconfidence (based on either financial or investment knowledge). With the broad set of controls described above, we find the use of margin among margin account holders is positively related to overconfidence measures. A one standard deviation increase in investment (financial) knowledge overconfidence is associated with a 9.4 (5.6) percentage point increase in the probability of using margin.

In the second part of the paper, we use data from a large discount broker over the period 1991 to 1996. These data were first used by Barber and Odean (2000), and have been subsequently used by a number of papers. These data allow us to test our two additional hypotheses: margin investors will speculate more and perform worse than well-calibrated investors. To do so, we analyze the trading and performance for the non-retirement accounts of over 43,000 investors; 66% have only margin accounts, 34% have only cash accounts, and 13% have experience using margin.[2]

To test our second prediction, we compare the monthly turnover and frequency of speculative trading for three groups of investors: investors with cash accounts (Cash Investors), investors with margin accounts but no observed margin experience in our sample period (Margin Account Investors), and investors with margin accounts and margin experience during our sample period (Margin Experience Investors). Monthly turnover is measured as the average of purchase and sale turnover, which is the value of purchases (or sales) scaled by the investor's position size. For each investor, we calculate average monthly turnover across months. Speculative trades are defined as sales for a gain followed by a purchase within three weeks (both the sale and purchase are considered speculative trades).[3] This definition filters out sales for a loss, which might occur to harvest a tax loss, and sales that are not followed by a purchase,

[1] See Section 2.2.1 for the details of these calculations.
[2] We do not directly observe margin trades. As a result, we identify investors as having experience with margin if we observe a short position in their monthly position statement or a trade in an option security.
[3] In unreported analyses, we use a more restrictive definition of speculative trades that additionally filters out sales for a loss, which might occur to harvest a tax loss, and partial sales for a gain which could be motivated by rebalancing. With the more restrictive measure, fewer trades are identified as speculative; all of our other results are qualitatively similar for both measures.

which might occur because an investor needs cash. For each investor, we calculate the percentage of all trades that are speculative.

In Figure 2, we show the average monthly turnover and percentage of all trades that are speculative. Consistent with our predictions that overconfidence will lead to greater use of margin and more active trading, we find that margin account investors, but especially margin experience investors, trade more and more speculatively than cash investors. The monthly turnover of cash, margin account, and margin experience investors are 6.9, 7.8, and 15.2% (respectively). All pairwise tests reject the null of equality. These same patterns are evident in the proportion of trades that are speculative. The percentage of cash, margin account, and margin experience investors are 15.2, 17.9, and 29.7% (respectively). All pairwise tests reject the null of equality. In additional tests we control for investor characteristics (e.g., age, gender, marital status, income, wealth, etc.) and find the differences in Figure 2 are not affected much by these controls. In sum, we find strong support for our second prediction: Margin investors trade more frequently and more speculatively than other investors.

Frequent trading by margin investors might emanate from an information advantage or from overconfidence. In our theoretical setup, for investors with low precision information, overconfidence increases the use of margin and results in lower profits. In contrast, more precise information yields greater profits and, on average, greater use of margin. To better assess which motive is the more likely driver of margin use by individual investors, we analyze the performance of trades by investors in three trading groups describe above: cash investors, margin account investors, and margin experience investors. To do so, we construct a calendar-time portfolio that mimic the buys of cash investors by assuming the stock is purchased at the transaction price and sold three days later. We similarly construct a short portfolio, which mimics the sales of cash investors and closes the short position three days later. These long-short portfolios are constructed for each investor group, yielding a time-series of daily returns on the long-short portfolio. To assess the returns earned on these portfolios, we regress the daily returns less the risk-free rate on the market excess return to estimate a daily abnormal return (or CAPM alpha). We also estimate daily abnormal returns using the Fama and French (2015) five-factor model plus a momentum factor (labeled *FF5+Mom Alpha*).

In Figure 3, we present the daily abnormal returns from these strategies. All three groups of investors perform poorly, as the long-short portfolios earns economically large and statistically significant negative alphas ranging from 24.7 bps to 35.5 bps *per day*. Thus, individual investors perform poorly in general. Cash investors and margin account investors have similarly poor performance with daily abnormal returns around 25 bps per day. However, because margin account investors trade more than cash investors trading is arguably more detrimental to their performance. What's particularly remarkable is the poor security selection of margin experience investors; the long-short portfolio that mimics the trades of margin experience investors loses about 35 bps per day and the 10 bps spread between investors with margin experience and other investors is economically and statistically significant (p<.01). However, the performance penalty is compounded by the fact that margin experience investors trade at nearly twice the rate of other investors (see Figure 2). We interpret this evidence as providing strong support for our third prediction that (overconfident) margin investors perform worse than other investors.

Our study is related to two recent studies of leveraged trading in foreign exchange markets. Heimer and Simsek (2019) analyze the effect of leverage restrictions in the retail foreign exchange market and find leverage constraints reduce trading volume and improve traders' average monthly returns. We extend this work by analyzing the use of leverage in the trading of common stock. Importantly, we provide evidence that overconfidence is a likely mechanism driving these results as we show margin investors exhibit higher levels of overconfidence than other investors. Heimer and Imas (2018) argue that behavioral biases might cause leveraged investors to perform poorly. To test this conjecture, they use the forex dataset and an experimental market to analyze the disposition effect and document investors who use leverage have a stronger disposition effect. We find support for their findings as margin investors have a stronger disposition effect than cash investors.

Our paper fits into the large literature on the behavior and performance of individual investors. In theory, overconfident investors will trade to their detriment (Odean 1998; Gervais and Odean 2001; Caballe and Sakovics 2003).[4] Consistent with the idea that individual investors are overconfident about their ability and trade to their detriment, many studies find individual investors earn poor returns both before and after transaction costs (Barber and Odean 2001, 2008; Grinblatt and Keloharju 2000, 2009).[5] (See Barber and Odean (2013) for a review of this literature.) We contribute to this literature by documenting an important interaction between leverage and overconfidence. Leverage is particularly appealing to overconfident investors.[6]

Though we focus on the overconfidence and margin use of retail investors, institutions may also suffer the consequences of taking leveraged risks that overconfidence causes them to underestimate. A possible example of this is Long-Term Capital Management (LTCM) which combined absolute-return trading strategies with high financial leverage that were initially successful but resulted in $4.6 billion in

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[4] Other models that consider investor overconfidence include DeLong, Shleifer, Summers, and Waldman (1991), Benos (1998), Kyle and Wang (1997), Daniel, Hirshleifer, and Subramanyam (1998, 2001).

[5] There is evidence that the buy-sell imbalance of individual investors in the U.S. positively predicts short-term returns (Barber, Odean, & Zhu 2008; Kelley and Tetlock 2013; Kaniel, Saar, & Titman 2008). Barber, Odean, & Zhu 2008 find the buy-sell imbalance negatively predicts returns at longer horizons.

[6] We show that overconfidence can lead investors to trade on margin. Cognitive dissonance could create a feedback loop in which trading on margin increases investor overconfidence. The basic idea is that most people want to maintain a positive self-image as a reasonable person. It could be perceived as unreasonable to trade on margin if one expected to lose money doing so. Therefore, to resolve cognitive dissonance and maintain a self-image as a reasonable person, an investor who is already trading on margin might convince himself that he has superior ability.

losses in the wake of the 1997 Asian financial crisis. Amid concerns of systemic effects of a LTCM failure, the Federal Reserve Bank of New York organized a bailout of $3.6 billion by LTCM's major creditors in 1998.

Our results may extrapolate to other markets. In housing markets, where leverage is readily accessible and often used, overconfident homebuyers might use more leverage, speculate more, and thereby potentially facilitate the formation of a bubble. Consistent with the idea that mistaken beliefs contributed to the housing bubble, Cheng, Raina, and Xiong (2014) show midlevel managers in securitized finance did not exhibit awareness of problems in housing markets in 2004-2006 period and certain groups were aggressive in increasing their exposure to housing during the pre-crisis period. In corporations, overconfident CEOs make poor decisions (Roll 1986; Malmendier and Tate 2005, 2008, 2009; Ben-David, Graham, and Harvey 2013). Overconfident CEOs might leverage their hubris, further exacerbating its deleterious effects on decision making. Consistent with this idea, Ben-David, Graham, and Harvey (2013) document that overconfident CEOs are more likely to use leverage. Ho, Huang, Lin, and Yen (2016) find overconfident bank CEOs were more likely to increase leverage and weaken lending standards leading up to the 2007-2009 financial crisis, making them more vulnerable to financial crisis shocks.

While we focus on margin trading on the level of individual investors, others look at the aggregate effects of margin trading. Kahraman and Tookes (2017) document that margin traders in India provide liquidity to other traders except during market crises. Three recent papers examine margin trading during the 2015 Chinese stock market bubble and crash. Hansman, Hong, Jian, Liu, and Meng (2019) find that relaxation of margin constraints contributed to the bubble and that unconstrained speculators front-ran predictable price increases in marginable stocks; Bian, Da, Lou, and Zhou (2019) find that during the crash there was a high correlation in the returns of stocks that shared a significant overlap in the investors who owned the stocks on margin; and Bian, He, Shue, and Zhou (2018) report that leverage induced sales contributed to the crash with stocks disproportionately held by margin investors experiencing abnormal price declines followed by reversals.

We do not claim that all investors who use leverage are overconfident. In theory, well-calibrated investors with superior skill or information might benefit from the use of margin. We do argue that overconfident investors are more likely to use leverage and that in the domain we study, individual investors with nonretirement brokerage accounts, it is plausible that overconfidence is the dominant motivation for the use of leverage. Supporting this conjecture, we find that margin investors are more overconfident, trade more and more speculatively, and perform worse than other investors.

1. The Model

In this section, we sketch out a model in which overconfident traders face an exogenous budget constraint which yields testable predictions. The model draws on features of models in Diamond and Verrecchia (1981), Hellwig (1980), Odean (1998) and Eyster, Rabin, and Vayanos (2019). The details of the model and proof of propositions are provided in the appendix.

A riskless asset and one risky asset are exchanged in one round of trading at time $t = 1$. Consumption takes place only at $t = 2$, at which time the riskless asset pays 1 unit per share and each share of the risky asset pays $\tilde{v} \sim N\left(\mu_0, {}^{1}/_{\lambda_0}\right)$. The riskless interest rate is assumed to be 0. There are N investors; we analyze the limit economy where $N \to \infty$. Thus, each investor correctly assumes that his own demand does not affect prices. At $t = 0$, each trader has an endowment of f_0 of the riskless asset and of $x_0 = 0$ of the risky asset, the net supply of which is assumed to be zero, known, and unchanging. Thus, each trader's wealth at $t = 0$ is $W_0 = f_0$.

Prior to trading at $t = 1$, each trader, j, receives one of $M = 2$ private signals corresponding to his type, $\tilde{s}_j = \tilde{v} + \tilde{\varepsilon}_m$, $m = H, L$, where $\tilde{\varepsilon}_m$ has the objective distribution $\tilde{\varepsilon}_m \sim \mathrm{N}\left(0, {}^{1}/_{\lambda_m}\right)$ and $\lambda_H > \lambda_L$ (i.e., H is higher precision signal than signal L). Traders differ not only in the precision of their signals but also in their beliefs about those precisions. Traders believe the distribution of their signal to be $\tilde{\varepsilon}_m \sim \mathrm{N}\left(0, {}^{1}/_{\gamma_m \lambda_m}\right)$; $\gamma_m = 1$ corresponds to rational beliefs and $\gamma_m > 1$ to overconfidence. In this analysis we assume that γ_H is always 1; thus traders receiving low precision signals may be overconfident. As discussed in Odean (1998), the differing precision of private signals in this model can alternatively be interpreted as differing abilities to interpret public information.

All traders have constant absolute risk aversion (CARA) utility over their wealth at $t = 2$ with a risk-aversion coefficient of r, i.e., the utility of trader j is $U_j = -\exp\left(-rW_{2,j}\right)$. Our model departs from Odean (1998) and follows Eyster, Rabin, and Vayanos (2019) in that traders ignore the signals of others and do not attempt to infer the signals of others from prices when they trade. Each trader j solves:

$$\max_{x_{1j}} E\left[-\exp\left(-rW_{2,j}\right) | s_j\right] \text{ subject to } P_1 x_{1,j} + f_{1,j} \leq f_{0,j} \tag{1}$$

When solving the maximization problem, each trader conjectures that price is a linear function of his private signal. An equilibrium is obtained because traders believe that they are behaving optimally, even though they are not. The equilibrium and proofs are presented in the appendix.

In the propositions, we analyze the effects of moderate degrees of overconfidence, that is overconfidence in the region close to $\gamma = 1$ for Low information type traders.

We define use of margin by trader j to be trader j buying a position in the risky asset with value greater than trader j's initial wealth in the riskless asset, i.e., $P_1 x_{1,j} > f_0 = W_0$. To simplify our analysis of margin use, we assume that $\mu_0 \gg {}^{\gamma_L}/_{\lambda_0}$, which holds true if the probability of zero payoff is sufficiently low, provided overconfidence of the low type (γ_L) is sufficiently low as well. This leads to three propositions.

Proposition 1a: *Low information traders' trading volume increases in overconfidence*.

Proposition 2a: *Low information traders' expected profit decreases in overconfidence*.

Proposition 3a: *Low information traders' probability of using margin increases in overconfidence*.

These three propositions are the main focus of our empirical tests.

Overconfident traders behave as if their signals were more precise than they actually are and place larger trades (in absolute value) than if they were not overconfident. This leads to greater trading and use of margin. Misinterpreting the precision of their signals, leads to suboptimal behavior that lowers expected profits.

As discussed in the introduction, investors who are not overconfident might use margin because they have better information. This is true in our model.

Proposition 1b: *Low information traders' trading volume increases in signal precision if* $\gamma_L \leq 2$.

Proposition 2b: *Low information traders' expected profit increases in signal precision for* $\gamma_L = 1$.

Proposition 3b: *Low information traders' probability of using margin increases in signal precision if* $\gamma_L \leq 2$.

While both overconfidence and greater signal precision can lead to greater use of margin, overconfidence is coupled with lower expected profits while greater signal precision with higher expected profits when overconfidence is not too high. We can, therefore, analyze the profitability of retail investors who use margin (versus those who don't) to understand whether their use of margin is more likely to be motivated by overconfidence or superior information.

2. Data

1.1 FINRA Investor Survey

Our first dataset is a 2015 investment survey of 2000 investors who have non-retirement brokerage accounts in the U.S. administered by the FINRA Investor Education Foundation (FINRA Investor Survey). The FINRA Investor Survey is a follow-up to the 2015 FINRA State-by-State Survey of about 500 adults per state (about 25,000 total). FINRA conducted a follow-up Investor Survey of 2,000 investors in the State-by-State Survey who indicated they had a non-retirement brokerage account. Both surveys are conducted online and respondents were contacted via email. The response rate for the FINRA State-by-State Survey is about 3%, and the response rate for the follow-up FINRA Investor Survey is 38%.

We match the answers in the Investor Survey to the State-by-State Survey to obtain information on respondents' access and use of margin, financial literacy, investment literacy, demographics, risk preferences, and trust in financial markets or regulation. Our main analysis is based on 1601 observations for which we have data on all control variables used later in our analyses. (The univariate results for the broader sample are very similar to those presented in the main analysis.)

In Table 1, we provide a variable dictionary and break variables into three broad groups: measures of margin availability and experience (Panel A), financial/investment literacy, self-assessment, and overconfidence measures (Panel B), and demographic information and risk preferences (Panel C).

We present descriptive statistics for the sample in Table 2. In Panel A, we note that 37.2% of respondents answer "Yes" to having the ability to buy stock on margin, 31.5% do not have the ability to buy stock on margin (*nomarginacc*), and 31.4% do not know if they have the ability to purchase on margin (*dnkmarginacc*).[7] Of the 37.2% (595 respondents) who answer "Yes" to having the ability to buy stock on margin, 48.1% (286 respondents) answer "Yes" to "Have you made any securities purchases on margin?". Thus, 17.9% of the 1601 investor survey sample have made purchases on margin.

We use three measures of overconfidence based on investment literacy, financial literacy, and personal performance expectations (respectively *OC_invlit*, *OC_finlit,* and *OC_perf*). Overconfidence in investment literacy is measured using a self-assessment of investment knowledge and a ten question investment literacy quiz administered as part of the Investment Survey. The self-assessment asks respondents "On a scale from 1 to 7, where 1 means very low and 7 means very high, how would you assess your overall investment knowledge?". The average response for respondents is 5.06 (*invself_score*). The investment literacy quiz asks respondents ten questions about investment concepts that are more detailed than those covered in the financial literacy quiz. The questions cover the following topics: stocks, bonds, bankruptcy, risk/return relation, asset class returns, inflation rates, nominal/real returns, municipal bonds, short selling, and margin buying. (See the appendix for the full text of the literacy questions.) The average respondent correctly answers 4.9 of 10 questions for a score of 49.8% (*invlit_score*). We convert the self-assessment and quiz scores to percentile ranks. Overconfidence in investment literacy is measured as the difference between the two percentile rank variables:

$$OC\_invlit = invself\_perc - invlit\_perc. \qquad (2)$$

Overconfidence in financial literacy is measured using a self-assessment of financial knowledge and a six question financial literacy quiz administered as part of the State-by-State Survey. The self-

[7] Nine respondents answered "prefer not to say." We group these respondents with the "do not know" respondents.

assessment asks respondents "On a scale from 1 to 7, where 1 means very low and 7 means very high, how would you assess your overall financial knowledge?". The average response for respondents is 5.87 (*finself_score*). The financial literacy quiz asks respondents six questions about basic financial literacy that address compound interest, inflation, bond/interest rate relations, consumer loans, mortgages, and investment in own-company stock. (See the appendix for the full text of the literacy questions.) The average respondent correctly answers 4.4 of 7 questions for a score of 72.9% (*finlit_score*). To measure overconfidence in financial literacy, we convert the self-assessment score and the financial literacy score to percentile ranks (*finself_perc* and *finlit_perc*). Overconfidence in financial literacy is a person's percentile rank in self-assessment of financial knowledge less the percentile rank on the financial literacy quiz:

$$OC\_finlit = finself\_perc - finlit\_perc. \tag{3}$$

The overconfidence measure allows us to assess cross-sectional variation in overconfidence, but does not allow us to test whether the sample is overconfident on average since, by construction, the overconfidence measure has a mean of zero for the sample.[8]

Overconfidence in the context of our theoretical model is the belief that one can better predict the future performance of a stock than is actually the case. Our two main measures of overconfidence, *OC_invlit* and *OC_finlit*, measure overconfidence in one's investment or financial knowledge rather than one's stock picking ability. It is likely that investors who overestimate how much they know about investments and finance also overestimate the probability that they can pick stocks that will beat the market. Consistent with the idea that miscalibration is correlated within the finance and investment domain, we find our two measures of overconfidence have a positive correlation of 55.2%. Thus, we believe the two overconfidence measures provide a noisy but reasonable proxy for overconfidence in one's stock picking ability. The noise in our measures will cause us to underestimate the effect of overconfidence in one's stock picking ability on the probability of margin use.

As a third measure of overconfidence, we identify investors who expect to perform better than the market as a whole based on the following survey question: "Over the next 12 months, how well do you expect your portfolio of investments to perform?" Respondents can choose worse than the market as a whole, about the same as the rest of the market, or better than the market as a whole. We label this variable as overconfidence in performance (*OC_perf*) as there is little evidence that investors can systematically beat the market (particularly after fees).[9] Almost 29% of investors expect to perform better than the market

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[8] The mean overconfidence measure for our sample will differ from precisely zero because we calculate percentile ranks for all available respondents but only analyze those with available control variables. The percentile ranks on *finlit_score*, *finself_score*, *invlit_score*, and *invself_score* of approximately 0.52 to 0.54 indicate the respondents with available control data are slightly above average on these dimensions.

[9] See Barber and Odean (2013) for a review of the evidence on the performance of individual investors.

as a whole. It's possible that investors who use margin leverage their investment in the market and believe the market will increase in the next 12 months. We cannot rule this possibility out and, as a result, prefer our first two measures of overconfidence. Nonetheless, overconfidence would also lead investors to incorrectly anticipate market-beating returns from their trades. Our empirical analysis of trades by investors with margin experience indicates trading causes them to underperform, rather than outperform, the market.

In Panel C of Table 2, we present demographic information on the sample. The sample is well-educated (64% have a college degree), white (80%), mostly male (58%), and mostly married (70%). 39% of respondents have children as dependents. About half of respondents are over the age of 55. The portfolio size in the non-retirement account is greater than $250,000 for 36% of respondents.

In Panel D of Table 2, we present descriptive statistics on risk and trust measures for the sample. We measure risk attitudes using the response to the following question: "Which of the following statements comes closest to describing the amount of financial risk that you are willing to take when you save or make investments?". Respondents answers include: Take substantial financial risks expecting to earn substantial return (*High Risk*, 11.4%), Take above average financial risks expecting to earn above average return (*Above Ave.*, 33.2%), Take average financial risks expecting to earn average return (*Ave. Risk*, 48.3%), and Not willing to take any financial risks (*No Risk*, 7.1%). Most of the sample has more than a 50% allocation to stock (*>50% Stock*, 62%) and only 4% have no stock allocation (*No Stock*).

We measure trust in markets based on the answer to the following question: "How confident are you that U.S financial markets offer good long-term opportunities for investors." Respondents answer using a 10-point Likert scale ranging from 1 (Not at all confident) to 10 (Extremely Confident). The average response is 7.2 (*TrustMkt)*. We use the average response to three questions regarding investors trust in regulation. Respondents assess whether "financial markets are effectively regulated," "regulators are able to keep up with new market developments," and regulators are "looking out for ordinary investors" using a 10-point Likert scale. We average the response to the three questions to create a variable that measures trust in regulation (*TrustReg*), which has an average value of 5.7 across respondents.

1.2 Discount Broker Data

Our second dataset comes from the discount broker dataset first used in Barber and Odean (2000), but used in a number of other subsequent studies which are reviewed in Barber and Odean (2013). The dataset contains information on trades and monthly positions from 1991 to 1996 for about 68,000 investors and 158,000 accounts. For a subset of the data, we have demographic data from a market research firm and survey responses completed when the account was opened.

We restrict our analysis to about 43,000 investors with nonretirement accounts since the motivation for investment and trading may differ in retirement and nonretirement accounts. This definition also lines up with the survey sample, which consists of investors with investments in nonretirement accounts.

Including retirement accounts as cash accounts in our analysis does not materially affect our results. We also require that an investor hold only one type of non-retirement account (margin or cash) and place at least one stock trade during the sample period.[10] We do not directly observe the use of margin by margin investors. As a proxy for margin experience, we identify investors that have a short stock position in their monthly position statement (denoted by a negative stock balance) or trade options.[11] The basic idea is investors who are willing to short stocks or trade options are also more likely to use margin when trading.

In Table 3, we provide variable definitions for the broker dataset. The margin variables are presented in Panel A, and trading activity variables in Panel B. Turnover is measured on a monthly basis as the average of purchase and sales turnover as in Barber and Odean (2001). Speculative trades are complete sales for a gain followed by a purchase within three weeks as in Odean (1999) and purchases preceded by a complete sale for a gain in the prior three weeks. Requiring a gain filters out sales that might be done to harvest a tax loss, requiring complete sales filters out rebalancing trades, and requiring a purchase within three weeks of the trade filters out liquidity-motivated sales. As in Odean (1998), the proportion of gains realized (*PGR*) is the ratio of realized gains divided by the sum of realized gains and unrealized gains; both the numerator and denominator are counted only on days with a sale. There is a similar calculation for the proportion of losses realized (*PLR*).

Returns after trade (Panel C) are calculated in event time from the day of trade (t=0). On the day of trade, the return is calculated from the transaction price to the stock's closing price. On subsequent days, we use the CRSP return. We then calculate the event-time abnormal return following a buy over the horizon (0,h) as:

$$R^b(0,h) = \prod_{t=0}^{h}(1 + r_{it}) - \prod_{t=1}^{h}(1 + r_{mt}), \tag{4}$$

Where r_{it} is the return of stock i on day t and r_{mt} is the CRSP value-weighted market index. We also construct calendar-time portfolios that mimic the buys and sells of different groups of investors, which we describe in detail later. Our return calculations do not consider commissions; including commissions will disproportionately reduce the net returns of more active investors.

Demographic variables are presented in Panel D. In later analyses we use these demographic variables as controls for investor characteristics. While descriptive statistics on investor knowledge and experience are based on averages of the 4-point scale, the control variables use dummy variables for each category. We also use dummy variables for each income bin and the log of wealth. When we are missing

[10] We define cash accounts as accounts with the variable type=C or type2=CA and margin accounts as accounts with type=M or type2=MA.
[11] Options trading is based on the broker product codes (OEQ, OFC, OIC, OIN, OPO). Virtually all of these trades occur in margin accounts, but 413 investors with only cash accounts have trades with these product codes. We exclude these investors from our analysis.

information for a particular variable, the variable is set to the sample mean and we introduce a missing dummy variable for each control variable that takes a value of one if the control variable is missing. To assess robustness of our results, we also conduct analyses based on a limited sample for which we have all control variables.

In Table 4, we present descriptive statistics on the investors meeting the sample requirements described above. In Panel A, we see that about 65.9% of investors have margin accounts and 13.3% of investors have margin experience. In Panel B, we see that the average investor has monthly turnover of 8.5% (annual turnover of about 102%), 18.5% of trades are speculative, the average investor is more likely to realize gains than losses (*PGRtoPLR* = 1.907), and the average portfolio size is just under $50,000. (The number of observations on the ratio of *PGRtoPLR* drops because a household must sell a stock for a loss to compute the ratio since PLR appears in the denominator of the ratio.) In Panel C, we observe the average investor has poor trading ability as the returns after purchases are generally negative, which is consistent with the evidence in Odean (1999) and Barber, Lee, Liu, and Odean (2008). In Panel D, we observe the sample consists mostly of men and of people who are married. The average investor is 41 years and reports an income of about $74,000; 22.7% of investors have children in the household. For a more limited sample, we have self-reported estimates of investment knowledge, investment experience, and wealth; the latter averages about $251,000.

2 Are Margin Traders Overconfident? Evidence from FINRA Investor Survey

2.1 Univariate Results

Our first test of the prediction that overconfident investors are more likely to use margin (i.e., Proposition 1) is a simple comparison of the three overconfidence measures (investment literacy, financial literacy, and performance) for those with or without margin accounts. In our main analysis, we test whether the overconfidence of 595 margin account holders differ from the 1006 other investors.[12]

The results of this analysis are presented in columns 1-6, Table 5. In Panel A, we analyze the three overconfidence measures based on investment literacy (*OC_invlit*), financial literacy (*OC_finlit*), and performance (*OC_perf*). For investment and financial literacy, we also present the components of the overconfidence measures. Those with margin account have great overconfidence in both investment and financial literacy. The differences in overconfidence in column 5 are quite similar for both measure (0.221 and 0.208, $p<.001$ in both cases). The magnitudes of these overconfidence differences represent more than half of a standard deviation for *OC_invlit* and *OC_finlit*, which are 0.364 and 0.388 respectively (see Table

[12] In appendix table A1, we compare the overconfidence of margin account holders to cash account holders and to investors who do not know if they have a margin account. Margin account holders are more overconfident than both other groups though the investors who answer 'do not know' to the margin question tend to have lower levels of financial literacy than others.

2). For both measures, the majority of the difference in overconfidence can be traced to the self-assessed knowledge of margin account holders (column 3), which are at the 68.7 percentile and 61.3 percentile for investment and financial self-assessed knowledge (respectively). Investment literacy is quite similar for margin account holders and other investors (54.9 vs 53.4 percentile respectively); the financial literacy of margin investors and is slightly lower than other investors (48.2 v. 55.1);.[13] Our third measure of overconfidence is whether an investor believes he will beat the market. On average, 39% of margin account holders expect to beat the market compared to 22.3% of other investors.

In Panel B, we present descriptive statistics on the demographic characteristics of margin account holders, other investors, and the difference between the two. Relative to other investors, margin account holders are more likely to be male, college-educated, nonwhite, younger, and have bigger portfolios. We observe little difference in the marital status of margin account holders. It is possible that these demographic characteristics are jointly correlated with a preference for margin accounts and overconfidence, which could yield a spurious difference in the overconfidence of margin account holders and other investors (a type of omitted variable problem). In later analyses, we control for these demographic differences and continue to find overconfidence is related to the probability of being a margin account holder. (As we discuss later, these demographic controls may overcorrect for a potential omitted variable because overconfidence might cause the demographic differences between margin account holders and others; for example, men might prefer margin accounts to women because they are more overconfident than women.[14])

In Panel C, we present descriptive statistics on risk and trust variables. Relative to other investors, margin account holders are more likely to express a willingness to take substantial financial risk (labeled "high risk" in the table), have a larger allocation to stocks, and have greater trust in markets and financial regulation. In contrast to the demographic controls, which might overcorrect for an unknown omitted variable, it's quite plausible that risk or trust preferences directly affect an investors willingness to open a margin account and are also correlated with overconfidence. We carefully consider this possibility in later analyses. To preview these results, risk preferences and trust do affect the propensity to open or use margin, but the effect of overconfidence survives granular controls for risk preferences or trust.

The above analysis analyzes margin account holders without conditioning on whether the investor has traded on margin. However, as seen in Figure 1, margin account holders with margin experience have lower levels of actual investment and financial literacy yet higher self-assessed levels than margin account holders who have not traded on margin. We focus on this difference by splitting the 595 investors with margin

[13] Recall that we drop survey responses with incomplete data and thus end up with percentile ranks that average slightly more than 0.50 for the final sample of 1601.

[14] We find mixed evidence that men are more overconfidence than women. Men expect to beat the market more often than women (30.5 v. 25.7%, $p<.05$), but men have less financial and investment overconfidence than women (differences of 0.071 and 0.049, $p<.05$).

accounts into the 286 investors with experience buying on margin and the 309 investors with margin accounts, but no experience buying on margin. We present these results in columns 7-12, Table 5.

In Panel A, we observe those with margin experience are consistently more overconfident than investors with margin accounts but no margin experience. The three key overconfidence variables (*OC_invlit*, *OC_finlit*, and *OC_perf*) all indicate those with margin experience are more overconfident than those without margin experience. Among investors with margin experience, self-assessed investment and financial knowledge fall at the 76th and 65th percentile (respectively), as shown in Figure 2, Panel B, and column 9, Table 5; both self-assessment scores are reliably higher than margin account holders without margin experience ($p<.001$). Interestingly, the margin experience investors have investment and financial literacy that rank at the 47th and 37th percentile (respectively), as shown in Figure 2, Panel B, and column 9, Table 5; both literacy scores are reliably lower than margin account holders without margin experience. In addition, margin experience investors expect to beat the market at much higher rates than those without margin experience (46.2% versus 32.4%).

In Panel B, we observe margin users tend to be younger with children and smaller portfolios. Otherwise, the demographic differences between those with margin experience and those without (columns 7-12, Table 5) are generally smaller than the differences between margin and cash accounts (columns 1-6). In Panel C, we observe the differences in risk, stock allocations, and trust between those with margin experience and those without (columns 7-12) are analogous to those observed between cash and margin account holders (columns 1-6).

2.2 Multivariate Results

2.2.1 Margin Account Use

The univariate results indicate margin investors, particularly those with margin experience, are more overconfident than other investors. In this section, we test Proposition 1 by analyzing whether overconfident investors are more likely to use margin after controlling for differences in demographics and preferences. To do so, we estimate a linear probability model where the dependent variable equals one if an investor opened a margin account (*marginacc*) and the key independent variable is a measure of overconfidence (e.g., overconfidence in investment literacy, *OC_invlit*):

$$marginacc = a + bOC\_invlit + X\Gamma + e, \quad (5)$$

where X is a matrix of control variables and Γ is a vector of coefficient estimates. We hypothesize the coefficient *b* is positive since overconfident investors are more likely to open a margin account. We also estimate regressions that use financial overconfidence (*OC_finlit*) and performance overconfidence (*OC_perf*) as the key independent variable.[15]

[15] To ensure results are not driven by the percentile transformation of self-assessment and quiz scores, appendix Tables A2 and A3 presents regression results using percentage scores on the literacy quizzes rather than percentile ranks and

We test whether investors with greater investment (financial) literacy are more likely to open a margin account by including both the investment (financial) overconfidence variable and the investment (financial) literacy variable in the regression:

$$marginacc = a + b\,OC\_invlit + c\,invlit\_perc + X\Gamma + e. \tag{6}$$

While we anticipate margin use will increase with overconfidence (b>0) the effect of increased literacy on margin use is less obvious. Investors with greater investment and financial literacy could use margin more because they have more investment skill (see Proposition 4 from our model). However, they could use margin less because they better understand the risks. It is also possible that investors who use margin may, as a result of greater involvement in investments, simply know more and score more highly on the literacy quizzes.

We first introduce demographic controls. As discussed above, it's possible that demographics are correlated with overconfidence and affect the choice to open a margin account for reasons unrelated to overconfidence. To address this concern, we introduce all of the demographic variables of Table 1, Panel C (*college*, *nonwhite*, *man*, *married*, *child*, age bin dummies, and portfolio size dummies).

We next introduce controls for differences in preferences across investors. As observed in our univariate analysis, there are large differences in the risk attitudes, stock allocations, and trust in financial markets and regulation of margin versus cash investors. To control for these differences, we introduce the risk and trust variables of Table 1, Panel D, as controls (*TrustMkt*, *TrustReg*, bins for risk preferences, and bins for stock allocation).

We present results in Table 6. Panel A presents results that use overconfidence in investment literacy, Panel B uses overconfidence in financial literacy, and Panel C uses overconfidence in performance. In column 1, we present the results of equation 5 with no controls. Consistent with Proposition 1, in all three panels, we see the measure of overconfidence is positively related to the probability of opening a margin account. For example, a one standard deviation increase of 0.364 in overconfidence in investment literacy (OC_invlit) is associated with a 14.2 percentage point increase in the probability of opening a margin account (0.364 * 0.390 = 14.2 ppt), which is a 38% increase relative to the baseline probability of having a margin account of 37.2%. The economic significance of the relation between financial overconfidence and the probability of having a margin account are similarly large; a one standard deviation increase of 0.388 in financial overconfidence yields a 12.5 ppt increase in the probability of opening a margin account (0.388*0.323 = 12.5) , which is a 34% increase relative to the baseline probability. In Panel C, we observe that investors who expect to beat the market have are 19.2 ppts more likely to have a margin account, which is a 52% increase relative to the baseline probability.

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overconfidence measures based on the difference between the self-assessment score and percentage quiz score. We obtain qualitatively similar results.

We estimate models with demographic controls (column 2), risk and trust controls (column 3), and both (column 4). In each of these models, we observe demographic controls reduce the size of the coefficient on the key overconfidence variables, but the coefficients remain economically and statistically large. For example, in column 4 where we include all controls, the effect of a one standard deviation increase of 0.364 in overconfidence in investment literacy times the coefficient of 0.217 is associated with a 7.9 ppt increase in the probability of having a margin account, which represents a 21% increase relative to the baseline probability of 37.2%.

In columns 5-9, we add investment literacy (Panel A) and financial literacy (Panel B) as independent variables and estimate the regression of equation 6. We observe more knowledgeable investors are more likely to open margin accounts. The inclusion of the investment and the financial literacy variables increase the economic significance of the overconfidence variable in all specifications.

2.2.2 Margin Use among Margin Account Holders

In Table 7, we analyze margin use among margin account holders. To do so, we use the sample of 595 investors with margin accounts and estimate the following two regressions:

$$marginexp = a + b\,OC\_invlit + X\Gamma + e, \text{ and} \tag{7}$$

$$marginexp = a + b\,OC\_invlit + c\,invlit\_perc + X\Gamma + e. \tag{8}$$

The dependent variable (*marginexp*) takes a value of one if the investor has experience buying on margin. These regressions test Proposition 1 by investigating whether more overconfident investors who have margin accounts are more likely to use margin to buy stock.

In Panel A, columns 1-4, we see the relation between overconfidence in investment literacy and the use of margin among margin account holders is positive and statistically significant. In columns 5-9, we introduce investment literacy as an additional independent variable. In these regressions, investment overconfidence retains its statistical significance and the relation between investment literacy and margin use is no longer statistically significant when we introduce risk/trust variables (columns 8-9). In Panel B, columns 1-4, we see that the relation between overconfidence in financial literacy and the use of margin among margin account holders is positive and statistically significant. In columns 5-9, we introduce financial literacy as an additional independent variable in the regressions; the overconfidence variable loses statistical significance when we introduce risk/trust variables (columns 8-9). However, this lack of statistical significance can be traced to a *negative* relation between the use of margin and financial literacy among margin account holders (i.e., margin use seems to appeal to the less financially literate). The negative relation between literacy and margin use among margin account holders is unique to financial literacy, perhaps because investment literacy is a more relevant than financial literacy for margin investors.

In Panel C, columns 1-4, we observe a positive relation between performance overconfidence and margin use among margin account holders. The relation is robust to the inclusion of demographic and risk/trust controls.

The economic significance of the relation between overconfidence and the use of margin is also large. In column 4, which yields the lowest coefficient estimates on the overconfidence variables we still see economically large effects. A one standard deviation increase in overconfidence in investment knowledge (0.364) is associated with a 9.4 percentage point increase in the probability of using margin (.094=.364*.257). The effect of a one standard deviation increase in financial knowledge overconfidence (0.388) is 5.6 percentage points (.056 = .388*.144).

To sum up, consistent with our first hypothesis there is strong evidence of a positive association between overconfidence and the propensity to open a margin account that is not explained by demographic or preference characteristics of investors. Among margin account holders, we generally find a positive relation between margin use and overconfidence. The relation between literacy and margin use among margin account holders is stronger when we use measures of overconfidence based on investment literacy.

We also generally find evidence that investors with higher levels of investment or financial literacy are more likely to open a margin account. However, among margin account holders the use of margin is only positively related to investment literacy.

We next analyze the investment behavior of margin account holders and those who use margin to assess whether margin users are skilled or overconfident investors.

3 Overconfidence and Margin Trading: Empirical Evidence from Broker Data

3.1 Univariate Results

We begin by presenting univariate statistics on the variables from the broker dataset conditional on investors with margin versus cash accounts. The results of this analysis are presented in Table 8, columns 1-6.

In Panel A, we analyze trading activity. Recall that overconfidence leads to more margin use and more trading (Propositions 2 and 3), but better information has the same effects (Propositions 4 and 5). We indeed observe that margin investors trade more and trade more speculatively[16] than investors with cash accounts. For example, the annual turnover of margin investors is 111.6% (9.3%*12), 28.8 percentage points higher than the annual turnover of cash investors (82.8% = 6.9%*12). About 20% of margin investors' trades are speculative compared to about 15% of cash investors' trades. In both cases, the differences in means are statistically significant (p<.01). Consistent with Heimer and Imas (2018), we find

[16] Note that in our formal model, all trading is speculative, that is, motivated by anticipated returns, not by liquidity needs, rebalancing, or taxes.

margin investors are more likely to sell winners rather than losers. Finally, we see that margin investors tend to have larger investment portfolios.

In columns 7-12, we analyze the difference in trading behavior of those with margin experience and margin account holders without margin experience (i.e., the conditional effect of margin experience among margin account holders). In all cases, we observe qualitatively similar differences between those with margin experience and those without. Investors with margin experience trade more, trade more speculatively, are more likely to sell winners, and tend to have larger portfolios than margin account holders without margin experience.

To determine whether the increased trading of margin traders is more likely traced to overconfidence (Proposition 3) or better information (Proposition 5), we analyze the returns from trading. In Panel B, columns 1-6, we observe both margin and cash investors have poor trading ability as the returns following buys are negative and the returns following sells are positive at all horizons that we analyze.[17] Consistent with the joint hypothesis that margin traders are more overconfident and that overconfidence decreases the expected profits of traders (Proposition 3), margin investors have poor security selection. Interestingly, margin and cash investors have similarly bad security selection following buys. However, margin investors have significantly worse security selection following sales. At a 4-day horizon (0,3), returns following sales by margin investors are 33.4 bps more positive than returns following sales by cash investors ($p<.01$). The results are similar at the longer horizons that we analyze. In columns 7-12, we observe similar patterns when we compare the stock selection ability of those with margin experience and those without though the magnitudes of the differences are much larger. As we will see in subsequent analyses, these differences remain robust to the introduction of numerous investor controls and the construction of calendar-time portfolio. These patterns support our conjecture that overconfidence leads to greater use of margin, more speculative trading, and lower profits. While it is also possible that better information at times leads to increased use of margin, these patterns do not provide support for the belief that margin investors are better informed.[18]

In Panel C, columns 1-6, we present demographic information on margin and cash investors. Sample sizes drop because we do not have demographic information on all investors. Nonetheless, the patterns in demographics are broadly consistent with those from the survey data. Margin investors are more likely to be younger single men without kids than cash investors. Margin investors also self-report higher levels of investment knowledge and investment experience echoing the results of the self-reported financial literacy and investment literacy from the investor survey. Margin investors tend to have higher incomes

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[17] Readers might notice the sample sizes are smaller in Panel B. This is because we only require one trade for each investor in our sample. Some investors will have only buys or only sells.

[18] Consistent with the idea that better information can lead to the profitable use of margin, Kelley and Tetlock (2016) document short selling by individual investors predicts negative returns.

and wealth, but these differences are more modest than the difference that we observe in portfolio size in Panel A. In columns 7-12, we observe very similar patterns in the differences we observe between those with margin experience versus those without (conditional on being a margin account holder).

3.2 Turnover, Speculative Trading, and the Disposition Effect

We further test Propositions 2 and 5 by estimating the following regression:

$$turnover = b_0 + b_1 marginacc + b_2 marginexp + X\Gamma + e. \tag{9}$$

The dependent variable is investor turnover. The key independent variables are dummy variables, *marginacc* and *marginexp*, which take a value of one if the investor has margin account and margin experience (respectively). The matrix *X* collects demographic controls (all variables from Panel C of Table 3) and Γ is the associated vector of coefficient estimates.

The results of this regression are presented in Table 9, columns 1-2. In column 1, we present a regression without control variables. In this regression, the intercept represents the turnover of cash accounts and the coefficient estimates on *marginacc* and *marginexp* provide an estimate of the incremental monthly turnover that we observe for margin investors and investors with margin experience. Margin investors with no margin experience (i.e., *marginacc=1*, *marginexp=0*) have monthly turnover that is 0.91 ppts greater than cash investors (p<.001); margin investors with margin experience (i.e., *marginacc=1*, *marginexp=1*) have turnover rates that are more than double those of cash or margin investors (p<.001). Importantly, when we introduce demographic controls, the estimated coefficient estimates are largely unaffected.[19]

In columns 3-4, we observe similar patterns for speculative turnover when we estimate the regression of equation 9 but replace the dependent variable with *spec_trade*. In columns 5-6, we observe similar patterns for the disposition effect when we use *PGRtoPLR* as the dependent variable in the regression.

In summary, margin investors and particularly those with experience trading on margin trade more frequently and more speculatively than cash investors. These conclusions are unaffected by the introduction of investor controls. These general patterns are consistent with the idea that either overconfidence and/or better information leads to greater margin use and more trading. We also find that margin investors are more likely to sell winners rather than losers relative to cash investors, which can lead to higher capital gains taxes.

To determine whether the high levels of trading by margin investors stems from their superior information or overconfidence, we analyze trade performance. In theory, overconfident investors will trade more and have lower profits (Propositions 2 and 3); better-informed investors will trade more and have

[19] In untabulated regressions, we drop investors with missing demographic information (about half of the sample) and find quantitatively similar results.

higher profits (Propositions 5 and 6). In the next two sections, we conduct two additional analyses to establish the empirical fact that margin traders have poor trade performance and conclude that for this group of investors overconfidence likely leads to the use or margin and poor trade performance.

3.3 Multivariate Analysis: Trade Performance

We estimate regressions that are similar in form to that of equation 9 but we use investor returns subsequent to a buy (or sell) as the dependent variable in the regression. In these regressions, the unit of observation is investor-trade and we cluster standard errors by the date of trade to address cross-sectional dependence in returns for trades executed on the same day. We analyze performance at horizons of 4, 6, and 21 days. (We also analyze longer horizons and do not find evidence that the poor performance at these short horizons is reversed. See appendix figure A1.)

The results of this analysis are presented in Table 10. In Panel A, column 1, we see that cash investors lose about 42.4 bps in the four days after buying a stock. Margin investors do somewhat better, but only if they have no margin experience and the improvement is marginally significant ($p<.10$) and leaves them with negative returns after purchases. Investors with margin experience have poor security selection, but it is not materially different from the poor security selection of cash investors. These results are similar when we introduce investor controls in column 2 or analyze longer horizons (columns 3-6).

Margin investors have significantly worse performance when we analyze their selling activity in Panel B. In column 1, we see that cash investors have poor security selection ability as the returns after sale are 72.2 bps. Investors with margin accounts but no margin experience have statistically worse sales timing as their sales earn 79.7 bps (72.2 + 7.5) after that trade date. Investors with margin experience have particularly bad sales timing as their sales earn 115.6 bps after the trade date (72.2 + 7.5 + 15.9). These conclusions are qualitatively similar when we introduce investor controls (column 2) or analyze longer horizons (columns 3-6).

In summary, margin investors have bad security selection as the mean returns after buys are negative and returns after sells are positive. Margin investors, particularly those with margin experience, have particularly bad sales timing relative to cash investors. We do not observe consistent differences in the purchase timing of margin and cash investors. Overall, we interpret the poor performance of margin investors as evidence consistent with our third hypothesis: overconfident margin traders will perform worse than other investors.

3.4 Calendar-Time Portfolios based on Trades

To more finely control for the factor exposure of stocks bought and sold by cash versus margin investors and to address concerns regarding cross-sectional dependence in the prior regression analyses, we construct calendar-time portfolios. Consider the trades of cash investors. We create a portfolio that mimics the buys of cash investors and holds the purchased stocks for three days. This analysis yields a time-series of daily returns on the buy-mimicking portfolio. We perform a similar analysis for margin investors with no margin experience and margin investors with margin experience. These three portfolios allow us to analyze the differences in the daily returns earned on the buy-mimicking portfolios of the three investor groups (cash investors, margin account without margin experience, margin account with margin experience).

We measure the daily abnormal return on these portfolios by estimating the following factor regressions:

$$R_{pt} - R_{ft} = \alpha + \beta(R_{mt} - R_{ft}) + sSMB_t + hHML_t + rRMW_t + cCMA_t + wWML_t + e_{pt}, \quad (10)$$

where *Rpt* is the return on the buy-mimicking portfolio, *Rft* is the riskfree rate, and *Rmt* is the return on the value-weighted market portfolio. The additional factors are long-short portfolios constructed to capture exposure to firm size (*SMB*), value versus growth (*HML*), profitability (*RMW*), investment (*CMA*), and momentum (*WML*) as discussed in Fama and French (2015). The independent variables are taken from Ken French's online data library.

The results of this analysis are presented in Table 11. We present daily percentage abnormal returns that use only the market excess return as an independent variable (CAPM alpha) and daily percentage abnormal returns based on the regression of equation 10 (FF5+Mom alpha). Focus first on Panel A, which presents results for a 4-day horizon. In columns 1-2, we see that the buy-mimicking portfolio for cash investors earns a -9.05 or -6.10 bps per day, an economically large shortfall that is statistically significant. In columns 3-4, we observe the sell-mimicking portfolio for cash investors earns 17.5 or 18.6 bps per day or an even bigger performance penalty than buys. In columns 5-6, we see the long-short portfolio (long the buy-mimicking portfolio and short the sell-mimicking portfolio) earns -26.5 or -24.7 bps per day. In summary, cash investors have dismal security selection ability and factor exposures do little to change this conclusion.

Margin investors without experience and margin investors with margin experience also have dismal security selection ability. However, the margin investors with margin experience are particularly bad. The last six rows of Panel A test for pairwise differences in the portfolio returns. Focus on columns 5-6, the long-short portfolios that summarize the evidence from the buy-mimicking and sell-mimicking portfolios. We observe that cash investors and margin investors without experience have very similar return experiences. However, margin investors with margin experience have reliably lower returns than cash investors or margin investors without margin experience. For example, the long-short portfolio that mimics the trades of margin investors with margin experience earns 10 bps less than that earned by cash investors or margin investors without margin experience.

In Panels B and C, we present results for the longer holding periods of 6 and 21 days. The daily alphas predictably decline as we consider longer holding periods. This occurs because the event-time returns for trades are quite similar at the different holding periods (see the univariate statistics of Table 8), which means the return shortfall per day is large at short horizons and smaller at longer horizons. Nonetheless, the general patterns are quite similar in that margin investors with margin experience have the most dismal security selection of the three groups.

Overall this evidence strongly supports the hypothesis that margin investors are overconfidence about their ability and hurt their performance through active trading.

4 Entertainment

We argue that overconfidence leads retail investors to use margin, to trade excessively, and to trade to their financial detriment. An alternative explanation for why retail investors actively engage in wealth reducing trades is that they finding trading entertaining, perhaps because they view it as an alternative form of gambling (Barber, Lee, Liu, & Odean 2008; Dorn and Sengmueller 2009; Dorn, Dorn, and Sengmueller 2015; Gao and Lin 2015). Of course, overconfidence and entertainment are not mutually exclusive; indeed, it is probably more entertaining to trade if one is overconfident about one's prospects for success. While we do not rule out entertainment as a partial driver of margin trading, there are three reasons why we don't believe that it can replace overconfidence in explaining retail investor margin trading.

First, entertainment does not explain why investors who are overconfident about their investment and financial knowledge are more likely to use margin.

Second, entertainment—unlike overconfidence—does not explain why investors who use margin underperform other investors.[20]

Third, if investors trade on margin for entertainment, knowing that doing so will likely reduce their wealth (i.e., they are not overconfident), then we might expect that the investors most likely to trade on margin would be those for whom the risks were lower relative to their total wealth. This is not the case. A subsample of the investors at the large discount brokerage self-report their total wealth. When we separately analyze the trading of investors whose portfolio size to wealth ratio is above the median of 17.7%, we find they are more, not less, likely to have margin experience. As reported in appendix Table A4, 61.1% of investors with margin experience have portfolio to wealth ratios above the median. Furthermore, margin experience investors with portfolio to wealth ratios above the median demonstrate similar tendencies to trade actively, trade speculatively, and exhibit a disposition effect as do margin experience investors with portfolio to wealth ratios below the median (appendix Table A5) and earn similarly poor returns from trading (appendix Table A6).

[20] An alternative explanation for why investors who use margin underperform is that great risk and the use of leverage can lead to poorer decision making (Ariely, Gneezy, Lowenstein, and Mazar 2009; Heimer and Imas 2018).

5 Conclusion

We develop a theoretical model of trading in which traders with below average information (or ability) are more likely to trade on margin if they are overconfident. Analyzing survey data of 1,601 retail investors with non-retirement accounts, we find that investors who are more overconfident about their investment knowledge, their financial knowledge, and their future returns relative to the market are more likely to have margin accounts and, conditional on having a margin account, are more likely to have traded on margin. Investors with margin accounts are more overconfident than other investors and those who have margin trading experience are more overconfident than investors who have margin accounts but have not traded on margin.

Our model also predicts that traders with below average information who use margin will engage in more active, speculative trading than those who do not use margin and will, on average, earn lower profits. To test this hypothesis, we examine the trading records for over 41,000 investors with non-retirement accounts at a large discount brokerage. We find that investors with margin accounts trade more actively, more speculatively, and less profitably than those with cash accounts and that among investors who have margin accounts, those with experience trading on margin trade more actively, more speculatively, and less profitably.

In sum, our evidence indicates that overconfidence—not better information—is a primary motivation for retail investors to trade, to their detriment, on margin. More generally, our analysis suggests overconfidence and leverage can be a dangerous mix.

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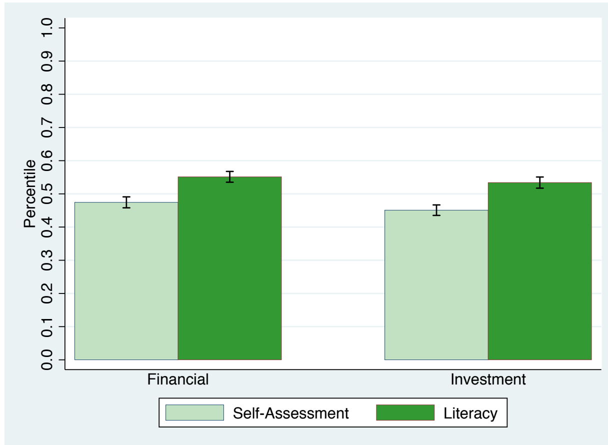
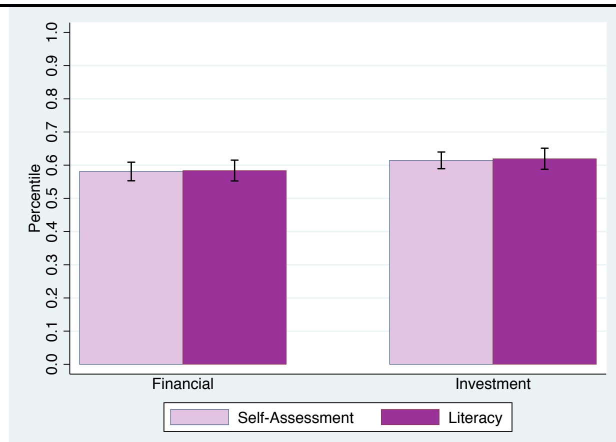
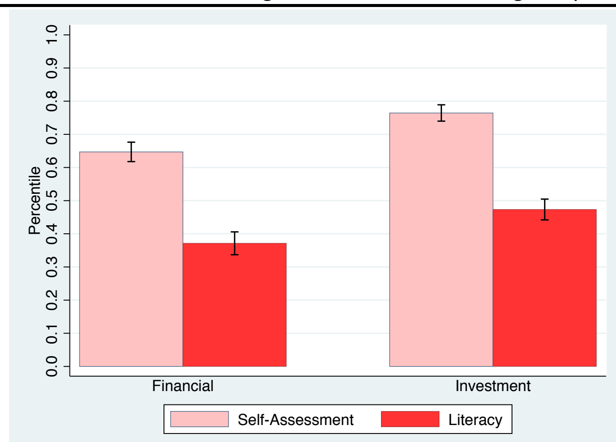


Panel A: Investors with cash accounts



Panel B: Investors with margin accounts but no margin experience



Panel C: Investors with margin trading experience

Figure 1. The Literacy and Self-Assessed Literacy of Margin Investors

The sample is 1,601 investors with non-retirement brokerage accounts; 1,006 with cash accounts (Panel A); 309 with margin accounts but no margin experience (Panel B); and 286 with experience buying on margin (Panel C). Investment literacy percentiles are based on a ten-question investment literacy quiz. Financial literacy percentiles are based on a six-question financial literacy quiz. Investment and Financial percentiles of self-assessment are based on self-assessments of knowledge using a seven point Likert scale. Whisker bars depict 95% confidence intervals.

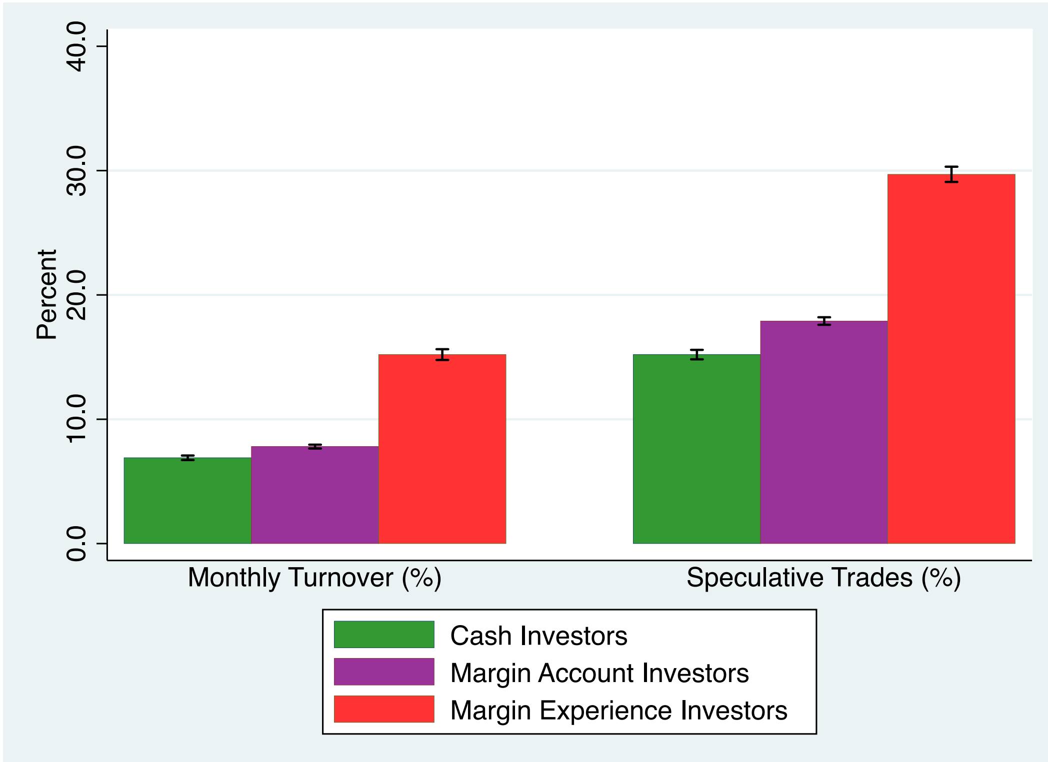


Figure 2. The Turnover and Speculative Trading of Investors
The three bars on the left present the monthly turnover (%). The three bars on the right present the percent of all trades that are speculative. Cash investors trade only in cash accounts. Margin account investors hold margin accounts but we do not observe short positions or options trades in their accounts. Margin experience investors are investors with margin accounts and experience trading options or shorting. Whiskers depict 95% confidence intervals.

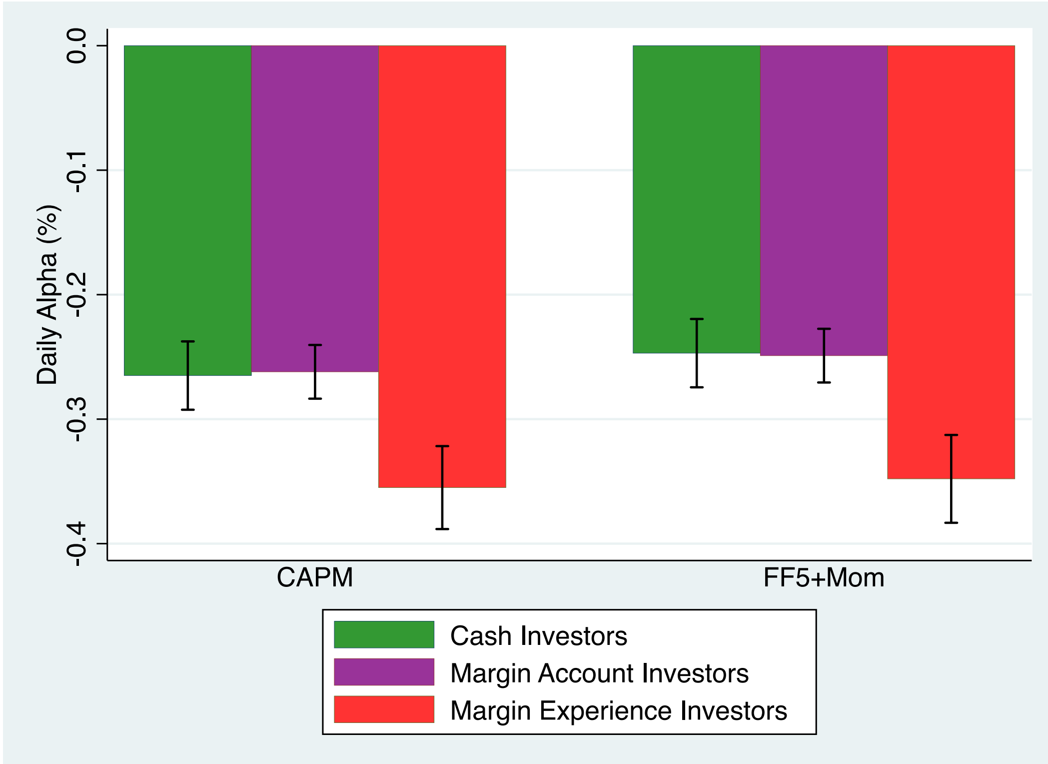


Figure 3. The Trade Performance of Margin and Cash Investors

The bars present the daily percentage alpha on a long-short portfolio that mimics the trades three investor groups and sells positions at market close three days after the trade, $t=0,3$. Cash investors trade only in cash accounts. Margin account investors hold margin accounts but we do not observe short positions or options trades in their accounts. Margin experience investors are investors with margin accounts and experience trading options or shorting. The long portfolio that mimics the buys of an investor group; the short portfolio mimics the sells. The daily percentage abnormal return (or alpha) on the portfolio is measured as the intercept from a regression of the portfolio excess return on the market excess return (CAPM alpha) or the portfolio excess return on the Fama-French five-factor model plus momentum (FF5+Mom). The trades data are from a discount broker. Whiskers depict 95% confidence intervals.

Table 1. NFCS Variable Definitions

The investment survey consists of 2,000 respondents who were selected based on having a non-retirement brokerage account from the 2015 National Financial Capability Survey. We restrict the sample to 1601 respondents with data on all variables.

Panel A: Margin Account and Margin Experience	
marginacc	Dummy variable that equals one if respondent has a margin account.
nomarginacc	Dummy variable that equals one if respondent does not have a margin account
dnkmarginacc	Dummy variable that equals one if respondent does not know if he has a margin account.
marginexp	Dummy variable that equals one if respondents has purchased stock on margin.
Panel B: Overconfidence Measures	
OC_invlit	*invself_perc - invlit_perc*
invself_perc	Percentile rank on self-assessment of financial knowledge
invlit_perc	Percentile rank on 7 question financial literacy quiz.
invself_score	Self-assessment of financial knowledge on a 7 point Likert scale.
invlit_score	Score on 7 question financial literacy quiz.
OC_finlit	*finself_perc - finlit_perc*
finself_perc	Percentile rank on self-assessment of financial knowledge
finlit_perc	Percentile rank on 7 question financial literacy quiz.
finself_score	Self-assessment of financial knowledge on a 7 point Likert scale.
finlit_score	Score on 7 question financial literacy quiz.
OC_perf	Dummy variable that equals one if respondent expects to perform better than the market.
Panel C: Demographic Variables	
college	Dummy variable that equals one if respondent completed college (or more).
nonwhite	Dummy variable that equals one if respondent is nonwhite.
man	Dummy variable that equals one if respondent is a man.
married	Dummy variable that equals one if respondent is married.
child	Dummy variable that equals one if respondent has children.
Age_35-54	Dummy variable that equals one if respondent is 35-54.
Age_55+	Dummy variable that equals one if respondent is 55 or older.
Port_50-250	Dummy variable that equals one if respondent's portfolio is \$50-\$250k.
Port_250+	Dummy variable that equals one if respondent's portfolio is > \$250k.
Panel D: Risk and Trust Variables	
Willingness to Take Risk:	
High Risk	Dummy variable that equals one if respondent is willing to take substantial financial risks.
Above Ave.	Dummy variable that equals one if respondent is willing to take above average financial risk.
Ave. Risk	Dummy variable that equals one if respondent is willing to take average financial risk.
No Risk	Dummy variable that equals one if respondent is not willing to take any financial risks.
Stock Allocation:	
>50% Stock	Dummy variable that equals one if respondent's stock allocation is more than half.
<50% Stock	Dummy variable that equals one if respondent's stock allocation is less than half.
No Stock	Dummy variable that equals one if respondent's stock allocation is zero.
TrustMkt	Response to long-term confidence in markets on 10-point Likert scale.
TrustReg	Mean response to 3 10-point Likert questions on trust in financial regulation

Table 2. Descriptive Statistics for Investment Survey Sample

See Table 1 for variable definitions. Std. Dev., Min., and Max are empty for dummy variables.

	N	Mean	Std. Dev.	Min.	Max
Panel A: Margin Account and Margin Experience					
marginacc	1,601	37.2%			
nomarginacc	1,601	31.5%			
dnkmarginacc	1,601	31.4%			
marginexp	1,601	17.9%			
Panel B: Overconfidence Measures					
OC_invlit	1,601	-0.001	0.364	-0.867	0.932
invself_perc	1,601	0.538	0.272	0.012	0.941
invlit_perc	1,601	0.540	0.278	0.009	0.994
invself_score	1,601	5.062	1.291	1.000	7.000
invlit_score	1,601	49.8%	21.5%	0.0%	100.0%
OC_finlit	1,601	0.000	0.388	-0.850	0.877
finself_perc	1,601	0.526	0.270	0.001	0.886
finlit_perc	1,601	0.525	0.282	0.009	0.893
finself_score	1,601	5.873	0.881	2.000	7.000
finlit_score	1,601	72.9%	23.6%	0.0%	100.0%
OC_perf	1,601	28.5%	45.1%	0.0%	100.0%
Panel C: Demographic Variables					
college	1,601	63.9%			
nonwhite	1,601	20.4%			
man	1,601	58.0%			
married	1,601	69.3%			
child	1,601	38.7%			
Age_35-54	1,601	32.9%			
Age_55+	1,601	49.5%			
Port_50-250	1,601	35.3%			
Port_250+	1,601	35.9%			
Panel D: Risk and Trust Variables					
Willingness to Take Risk:					
High	1,601	11.4%			
Above Ave.	1,601	33.2%			
Average	1,601	48.3%			
No Risk	1,601	7.1%			
Stock Allocation:					
>50% Stock	1,601	62.0%			
<50% Stock	1,601	34.2%			
No Stock	1,601	3.8%			
TrustMkt	1,601	7.217	1.978	1.000	10.000
TrustReg	1,601	5.671	2.337	1.000	10.000

Table 3. Discount Broker Variable Definitions

The main sample consists of 43143 housholds with only margin or only cash accounts from the discount broker dataset (see Barber and Odean 2001).

Panel A: Margin Account and Margin Experience	
marginacc	Dummy variable that equals one if household has only margin accounts
marginexp	Dummy variable that equals one if household has traded options or shorted stock
Panel B: Trading Activity	
turnover	Mean monthly turnover, calculated as the average of buy and sell turnover
spec_trade	The proportion of household trades that are speculative trades[1]
PGRtoPLR	The ratio of Proportion Gains Realized to Proportion Losses Realized[2]
tradesize	Mean trade size
numtrades	Mean number of trades per month
portsize ($000)	Portfolio size based on mean value of month-end positions
Panel C: Returns after Trade (%)	
$R^{b}(0,h)$	Return following a buy from day $t=0,h$ (0 is the trade day)
$R^{s}(0,h)$	Return following a sell from day $t=0,h$ (0 is the trade day)
Panel C: Demographic and Other Characteristics	
man	Dummy variable that equals one if respondent is a man
age	Age in years
married	Dummy variable that equals one if respondent is married
child	Dummy variable that equals one if respondent has children
knowledge	Self-assessed knowledge on a 4-point scale (4=excellent, 1=poor)
experience	Self-assessed experience on a 4-point scale (4=extensive, 1=limited)
income ($000)	Annual income based on midpoints ranging from $10k to $125k of 9 income bins
wealth ($000)	Self-reported wealth winsorized at the 1st and 99th percentile.

[1] Speculative trades are sales followed by a purchase wihin 3 weeks.

[2] The Proportion Gains Realized is the number of realized gains divided by the sum of realized gains and paper gains. There is a similar calculation for the Proportion of Realized Losses.

Table 4. Descriptive Statistics for Broker Dataset

See Table 3 for variable descriptions.

	N	Mean	Std. Dev.	Min.	Max
Panel A: Margin Account and Margin Experience					
marginacc	43,143	65.9%			
nomarginacc	43,143	34.1%			
marginexp	43,143	13.3%			
Panel B: Trading Activity and Portfolio Size					
turnover	43,143	0.085	0.127	0.000	1.000
spec_trade	43,143	0.185	0.238	0.000	1.000
PGRtoPLR	19,302	1.907	1.903	0.000	82.627
tradesize ($000)	43,143	9.171	17.575	0.003	1081.117
numtrades (monthly)	43,143	0.855	2.393	0.014	96.794
portsize ($000)	43,099	48.890	230.041	0.000	37994.650
Panel C: Returns after Trade (%)					
$R^b(0,3)$	37,048	-0.507	4.548	-87.700	91.931
$R^b(0,5)$	37,049	-0.541	5.245	-84.648	127.503
$R^b(0,20)$	37,049	-0.750	8.607	-99.942	198.989
$R^s(0,3)$	39,528	0.985	4.941	-71.320	200.244
$R^s(0,5)$	39,528	1.047	5.766	-71.291	298.942
$R^s(0,20)$	39,529	1.487	10.042	-91.556	369.693
Panel D: Demographic and Other Characteristics					
man	27,189	88.4%			
age	26,005	50.026	13.450	22.000	94.000
married	24,056	71.8%			
child	31,598	22.7%			
knowledge	15,256	2.593	0.822	1.000	4.000
experience	14,715	2.715	0.745	1.000	4.000
income ($000)	27,323	74.101	34.545	10.000	130.000
wealth ($000)	15,208	251.326	478.821	7.500	4000.000

Table 5. Descriptive Statistics by Margin Account or Experience Status, Investor Survey

See Table 1 for variable definitions

	Margin Account Status, Full Sample						Margin Experience, Margin Account Holders					
	Cash Account		Margin Account		Difference		No Margin Exp.		Margin Exp.		Difference	
	Mean	N	Mean	N	Mean	t-stat	Mean	N	Mean	N	Mean	t-stat
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Overconfidence Variables												
OC_invlit	-0.083	1006	0.137	595	0.221	12.27	-0.005	309	0.291	286	0.296	10.18
invself_perc	0.451	1006	0.687	595	0.236	18.45	0.615	309	0.764	286	0.150	8.33
invlit_perc	0.534	1006	0.549	595	0.015	1.05	0.619	309	0.473	286	-0.146	-6.40
OC_finlit	-0.077	1006	0.131	595	0.208	10.73	-0.003	309	0.276	286	0.278	8.74
finself_perc	0.474	1006	0.613	595	0.138	10.21	0.581	309	0.647	286	0.066	3.20
finlit_perc	0.551	1006	0.482	595	-0.070	-4.81	0.584	309	0.371	286	-0.212	-8.96
OC_perf	0.223	1006	0.390	595	0.167	7.28	0.324	309	0.462	286	0.138	3.48
Panel B: Demographic Variables												
college	0.620	1006	0.671	595	0.050	2.03	0.686	309	0.654	286	-0.032	-0.84
nonwhite	0.145	1006	0.303	595	0.157	7.69	0.278	309	0.329	286	0.050	1.34
man	0.530	1006	0.666	595	0.136	5.36	0.686	309	0.643	286	-0.043	-1.10
married	0.687	1006	0.704	595	0.017	0.73	0.699	309	0.710	286	0.011	0.29
child_dum	0.299	1006	0.534	595	0.235	9.60	0.392	309	0.689	286	0.297	7.59
Age_35-54	0.298	1006	0.382	595	0.083	3.44	0.350	309	0.416	286	0.067	1.67
Age_55+	0.580	1006	0.353	595	-0.227	-8.98	0.492	309	0.203	286	-0.289	-7.72
Port_50-250	0.359	1006	0.343	595	-0.016	-0.65	0.282	309	0.409	286	0.128	3.30
Port_250+	0.325	1006	0.415	595	0.090	3.64	0.463	309	0.364	286	-0.099	-2.46
Panel C: Risk and Trust Variables												
Willingness to Take Risk:												
High	0.051	1006	0.222	595	0.171	10.76	0.081	309	0.374	286	0.293	9.18
Above Ave.	0.263	1006	0.447	595	0.184	7.67	0.430	309	0.465	286	0.035	0.85
Average	0.586	1006	0.309	595	-0.277	-11.13	0.456	309	0.150	286	-0.306	-8.53
No Risk	0.586	1006	0.309	595	-0.277	-11.13	0.456	309	0.150	286	-0.306	-8.53
Stock Allocation:												
>50% Stock	0.569	1006	0.706	595	0.137	5.52	0.654	309	0.762	286	0.109	2.92
<50% Stock	0.377	1006	0.284	595	-0.093	-3.79	0.327	309	0.238	286	-0.089	-2.42
No Stock	0.055	1006	0.010	595	-0.045	-4.53	0.019	309	0.000	286	-0.019	-2.38
TrustMkt	6.888	1006	7.775	595	0.887	8.88	7.476	309	8.098	286	0.622	4.06
TrustReg	5.263	1006	6.361	595	1.099	9.33	5.548	309	7.240	286	1.692	8.68

Table 6. Regressions of Margin Account Status on Overconfidence

The table presents linear probability models where the dependent variable is a dummy variable that takes a value of one if the household has margin account and zero for households without margin or do not know. The key independent variables are Overconfidence in Investment Literacy (Panel A), Financial Literacy (Panel B), and Performance (Panel C). Overconfidence in investment literacy is the difference between the percentile rank on a person's self-assessment of investment knowledge (invself_p) less the percentile rank on a person's score on a ten question financial literacy quiz (invlit_p). Overconfidence in financial literacy is the difference between the percentile rank on a person's self-assessment of financial knowledge (finself_p) less the percentile rank on a person's score on a six question financial literacy quiz (finlit_p). Panel D lists control variables. Demographic controls include dummy variables for college education, nonwhite, gender, marital status, presence of children, age bins (<35, 35-54, >54), portolio size bins (<$50k, $50-$250k, >$250k). Preference controls include dummy variables for willingness to take risks (none, average, above average, high), stock allocation in portfolio (none, <=50%, >50%), trust in markets (10 point Likert scale), and trust in regulation (10 point Likert scale).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Overconfidence in Investment Literacy, OC_invlit = invself_perc - invlit_perc								
OC_invlit	0.390***	0.282***	0.248***	0.217***	0.750***	0.571***	0.528***	0.444***
	(0.031)	(0.033)	(0.035)	(0.036)	(0.036)	(0.041)	(0.045)	(0.046)
invlit_perc					0.704***	0.586***	0.499***	0.431***
					(0.050)	(0.056)	(0.055)	(0.058)
Observations	1,601	1,601	1,601	1,601	1,601	1,601	1,601	1,601
R-squared	0.086	0.190	0.199	0.251	0.176	0.242	0.238	0.276
Panel B: Overconfidence in Financial Literacy, OC_finlit = finself_perc - finlit_perc								
OC_finlit	0.323***	0.245***	0.192***	0.183***	0.446***	0.358***	0.266***	0.246***
	(0.029)	(0.029)	(0.031)	(0.030)	(0.041)	(0.041)	(0.043)	(0.043)
finlit_perc					0.236***	0.234***	0.146**	0.129**
					(0.059)	(0.061)	(0.058)	(0.061)
Observations	1,601	1,601	1,601	1,601	1,601	1,601	1,601	1,601
R-squared	0.067	0.188	0.192	0.250	0.076	0.196	0.195	0.252
Panel C: Overconfidence in Performance, OC_perf (Expected to Outperform Stock Market)								
OC_perf	0.192***	0.129***	0.097***	0.073***	--	--	--	--
	(0.027)	(0.026)	(0.027)	(0.026)	--	--	--	--
Observations	1,601	1,601	1,601	1,601	--	--	--	--
R-squared	0.032	0.168	0.181	0.238	--	--	--	--
Panel D: Control Variables								
Demographic	NO	YES	NO	YES	NO	YES	NO	YES
Risk and Trust	NO	NO	YES	YES	NO	NO	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 7. Regressions of Margin Experience on Overconfidence

The table presents linear probability models where the dependent variable is a dummy variable that takes a value of one if the household has used margin and zero if the household has not; the sample consists of households with a margin account. Households with cash accounts are excluded. The key independent variables are Overconfidence in Investment Literacy (Panel A), Financial Literacy (Panel B), and Performance (Panel C). Overconfidence in investment literacy is the difference between the percentile rank on a person's self-assessment of investment knowledge (invself_p) less the percentile rank on a person's score on a ten question financial literacy quiz (invlit_p). Overconfidence in financial literacy is the difference between the percentile rank on a person's self-assessment of financial knowledge (finself_p) less the percentile rank on a person's score on a six question financial literacy quiz (finlit_p). Panel D lists control variables. Demographic controls include dummy variables for college education, nonwhite, gender, marital status, presence of children, age bins (<35, 35-54, >54), portolio size bins (<$50k, $50-$250k, >$250k). Preference controls include dummy variables for willingness to take risks (none, average, above average, high), stock allocation in portfolio (none, <=50%, >50%), trust in markets (10 point Likert scale), and trust in regulation (10 point Likert scale).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Overconfidence in Investment Literacy, OC_invlit = invself_perc - invlit_perc								
OC_invlit	0.503***	0.360***	0.291***	0.257***	0.658***	0.511***	0.342***	0.322***
	(0.047)	(0.058)	(0.059)	(0.062)	(0.081)	(0.086)	(0.090)	(0.091)
invlit_perc					0.260**	0.281**	0.082	0.115
					(0.114)	(0.121)	(0.111)	(0.121)
Observations	595	595	595	595	595	595	595	595
R-squared	0.149	0.213	0.277	0.296	0.157	0.221	0.277	0.297
Panel B: Overconfidence in Financial Literacy, OC_finlit = finself_perc - finlit_perc								
OC_finlit	0.410***	0.279***	0.162***	0.144**	0.210***	0.186**	0.024	0.049
	(0.044)	(0.051)	(0.058)	(0.059)	-0.077	-0.076	-0.078	-0.079
finlit_perc					-0.340***	-0.184	-0.260**	-0.194*
					-0.104	-0.113	-0.104	-0.113
Observations	595	595	595	595	595	595	595	595
R-squared	0.114	0.201	0.256	0.282	0.131	0.205	0.264	0.286
Panel C: Overconfidence in Performance, OC_perf (Expected to Outperform Stock Market)								
OC_perf	0.145***	0.109***	0.092**	0.086**	--	--	--	--
	(0.042)	(0.039)	(0.037)	(0.037)	--	--	--	--
Observations	595	595	595	595	--	--	--	--
R-squared	0.020	0.170	0.252	0.280	--	--	--	--
Panel D: Control Variables								
Demographic	NO	YES	NO	YES	NO	YES	NO	YES
Risk and Trust	NO	NO	YES	YES	NO	NO	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 8. Summary Statistics for Cash versus Margin Investors, Broker Dataset

See Table 3 for variable descriptions. Means are calcualted across investors. For each investor, turnover is average monthly turnover during the sample period. For each investor, returns after trade are averaged across all trades.

	Margin Account Status, Full Sample						Margin Experience, Margin Account Holders					
	Cash Account		Margin Account		Difference		No Margin Exp.		Margin Exp.		Difference	
	Mean	N	Mean	N	Mean	t-stat	Mean	N	Mean	N	Mean	t-stat
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Trading Activity and Portfolio Size												
turnover	0.069	14,716	0.093	28,427	0.024	19.72	0.078	22,691	0.152	5,736	0.074	31.76
spec_trade	0.152	14,716	0.202	28,427	0.051	21.15	0.179	22,691	0.297	5,736	0.118	33.83
PGRtoPLR	1.733	4,947	1.967	14,355	0.234	8.37	1.87	10,334	2.215	4,021	0.345	8.84
tradesize ($000)	6.972	14,716	10.310	28,427	3.337	21.29	9.411	22,691	13.866	5,736	4.456	12.10
numtrades (mthly)	0.546	14,716	1.015	28,427	0.469	22.33	0.819	22,691	1.79	5,736	0.971	17.38
portsize ($000)	35.158	14,716	54.932	28,427	19.774	10.88	49.028	22,691	78.288	5,736	29.26	4.00
Panel B: Returns after Trade (%)												
$R^b(0,3)$	-0.546	12,221	-0.488	24,827	0.058	1.14	-0.485	19,385	-0.499	5,442	-0.014	-0.21
$R^b(0,5)$	-0.567	12,221	-0.528	24,827	0.039	0.67	-0.519	19,385	-0.561	5,442	-0.042	-0.58
$R^b(0,20)$	-0.700	12,221	-0.772	24,827	-0.072	-0.75	-0.822	19,385	-0.597	5,442	0.225	1.93
$R^s(0,3)$	0.759	12,814	1.093	26,714	0.334	6.51	0.912	21,023	1.763	5,691	0.851	11.85
$R^s(0,5)$	0.829	12,814	1.152	26,714	0.323	5.18	0.979	21,023	1.791	5,691	0.812	10.38
$R^s(0,20)$	1.164	12,814	1.643	26,714	0.479	4.34	1.498	21,023	2.178	5,691	0.680	5.79
Panel C: Demographic and Other Characteristics												
man	0.867	9,708	0.894	17,481	0.027	6.41	0.888	14,107	0.918	3,374	0.03	5.64
age	51.066	9,308	49.447	16,697	-1.62	-9.19	49.616	13,466	48.74	3,231	-0.876	-3.42
married	0.744	8,613	0.703	15,443	-0.041	-6.88	0.706	12,464	0.691	2,979	-0.016	-1.66
child_dum	0.235	11,085	0.222	20,513	-0.013	-2.71	0.223	16,513	0.217	4,000	-0.006	-0.79
knowledge	2.492	4,539	2.635	10,717	0.143	10.23	2.592	8,343	2.787	2,374	0.196	9.39
experience	2.566	4,422	2.780	10,293	0.214	16.55	2.709	8,033	3.030	2,260	0.321	17.58
income ($000)	73.039	9,739	74.69	17,584	1.651	3.81	74.671	14,179	74.768	3,405	0.097	0.15
wealth ($000)	238.17	4,439	256.75	10,769	18.586	2.23	244.11	8,368	300.81	2,401	56.707	4.30

Table 9. Turnover, Speculative Trade, and the Disposition Effect for Cash versus Margin Investors

The unit of observation is household. The dependent variable is either mean monthly turnover (turnover in columns 1-2), proportion of trades that are speculative (columns 3-4), or the ratio of PGR to PLR (*PGRtoPLR* of columns 5-6). The key independent variables are *marginacc* , which equals one if the household has margin accounts, and *marginexp* , which equals one if the household has experience trading options or shorting stock. In the regressions without controls (columns 1, 3, and 5), the intercept can be interpreted as the mean value of the dependent variable for cash investors. Investor controls include variables from Table 3, Panel C (man, age, married, child_dum, knowledge, experience, income, wealth). In columns 2, 4, and 6, for each variable observations with missing data are assigned the mean value for the variable and a missing dummy variable equals one. Robust standard errors are in parentheses. ***, **, * significant at the 1%, 5%, 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep var:	*turnover*		*spec_trade*		*PGRtoPLR*	
cash (Intercept)	0.0691***	n.a.	0.152***	n.a.	1.733***	n.a.
	(0.001)		(0.002)		(0.022)	
marginacc	0.00910***	0.00787***	0.0269***	0.0271***	0.137***	0.134***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.029)	(0.030)
marginexp	0.0742***	0.0724***	0.118***	0.117***	0.346***	0.339***
	(0.002)	(0.002)	(0.003)	(0.004)	(0.039)	(0.039)
Investor Controls	No	Yes	No	Yes	No	Yes
Observations	43143	43143	43143	43143	19302	19302
R-squared	0.044	0.052	0.036	0.041	0.008	0.013

Table 10. Returns from Trading for Cash versus Margin Investors

The unit of observation is trade. The dependent variable is the return following a trade (the return on the traded stock minus a value-weighted market index). The key independent variables are *marginacc* , which equals one if the household has margin accounts, and *marginexp* , which equals one if the household has experience trading options or shorting stock. In the regressions without controls, the intercept can be interpreted as the mean return earned on trades in cash accounts. Investor controls include variables from Table 3, Panel C (*man* , *age* , *married* , *child_dum* , *knowledge* , *experience* , *income* , *wealth*); for each variable, observations with missing data are assigned the mean value for the variable and a missing dummy variable equals one. Standard errors are clustered by trading date and are robust to heteroscedasticity. Standard errors are in parentheses. ***, **, * significant at the 1%, 5%, 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Returns following Buys						
Dep. Var.:	*R^b (0,3)*		*R^b (0,5)*		*R^b (0,20)*	
cash (Intercept)	-0.424***	n.a.	-0.478***	n.a.	-0.567***	n.a.
	(0.047)		(0.053)		(0.101)	
marginacc	0.0526*	0.0621**	0.0567	0.0598*	0.0236	0.0268
	(0.030)	(0.030)	(0.036)	(0.036)	(0.062)	(0.062)
marginexp	-0.0249	-0.0326	-0.0123	-0.0310	0.0942	0.0924
	(0.033)	(0.032)	(0.036)	(0.036)	(0.059)	(0.060)
Investor Controls	No	Yes	No	Yes	No	Yes
Observations	675,490	675,490	675,490	675,490	675,490	675,490
Panel B: Returns following Sales						
Dep. Var.:	*R^s (0,3)*		*R^s (0,5)*		*R^s (0,20)*	
cash (Intercept)	0.722***	n.a.	0.724***	n.a.	0.927***	n.a.
	(0.047)		(0.057)		(0.116)	
marginacc	0.0747**	0.0758**	0.126***	0.130***	0.184***	0.186***
	(0.033)	(0.033)	(0.041)	(0.040)	(0.066)	(0.067)
marginexp	0.359***	0.361***	0.294***	0.296***	0.194**	0.212**
	(0.067)	(0.065)	(0.069)	(0.067)	(0.088)	(0.087)
Investor Controls	No	Yes	No	Yes	No	Yes
Observations	578,714	578,714	578,714	578,714	578,714	578,714

Table 11. Calendar-Time Portfolio Returns to Following Trades of Cash versus Margin Investors (Daily %)

The unit of observation is daily percent portfolio return. Portfolios are constructed by assuming trades occur at the transaction prices of investors (t=0). Divestment is assumed to occur 3 days (Panel A), 5 days (Panel B), or 20 days (Panel C) after the day of trade. For each horizon, we calculate the daily percentage abnormal return as the intercept in a regression of the portfolio excess return (return less the riskfree rate) on the market excess return (CAPM alpha) or the Fama-French five factors plus a momentum factor (FF5+Mom alpha). Standard errors are in parentheses. ***, **, * significant at the 1%, 5%, 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Buy		Sell		Buy - Sell	
	CAPM alpha	FF5+Mom alpha	CAPM alpha	FF5+Mom alpha	CAPM alpha	FF5+Mom alpha
Panel A: Follow trades and hold to day t+3: (0,3)						
(1) Cash investors	-0.0905***	-0.0610***	0.175***	0.186***	-0.265***	-0.247***
	(0.015)	(0.014)	(0.011)	(0.010)	(0.014)	(0.014)
(2) Margin account without experience	-0.0785***	-0.0465***	0.184***	0.202***	-0.262***	-0.249***
	(0.016)	(0.015)	(0.012)	(0.010)	(0.011)	(0.011)
(3) Margin account with experience	-0.0940***	-0.0586***	0.261***	0.289***	-0.355***	-0.348***
	(0.018)	(0.016)	(0.019)	(0.018)	(0.017)	(0.018)
(2) - (1)	0.0120	0.0144*	0.00901	0.0165*	0.00302	-0.00206
	(0.009)	(0.009)	(0.009)	(0.009)	(0.012)	(0.012)
(3) - (2)	-0.0155*	-0.0121	0.0773***	0.0872***	-0.0928***	-0.0993***
	(0.009)	(0.009)	(0.014)	(0.015)	(0.017)	(0.018)
(3) - (1)	-0.00345	0.00238	0.0863***	0.104***	-0.0898***	-0.101***
	(0.011)	(0.011)	(0.017)	(0.017)	(0.020)	(0.020)
Panel B: Follow trades and hold to day t+5: (0,5)						
(1) Cash account	-0.0612***	-0.0345***	0.116***	0.127***	-0.177***	-0.161***
	(0.014)	(0.012)	(0.010)	(0.009)	(0.011)	(0.011)
(2) Margin account without experience	-0.0548***	-0.0243*	0.130***	0.148***	-0.185***	-0.173***
	(0.015)	(0.013)	(0.011)	(0.009)	(0.009)	(0.009)
(3) Margin account with experience	-0.0644***	-0.0306**	0.177***	0.206***	-0.242***	-0.236***
	(0.017)	(0.015)	(0.017)	(0.015)	(0.013)	(0.013)
(2) - (1)	0.00639	0.0101	0.0144*	0.0218***	-0.00798	-0.0117
	(0.007)	(0.007)	(0.007)	(0.007)	(0.010)	(0.010)
(3) - (2)	-0.00956	-0.00627	0.0473***	0.0575***	-0.0569***	-0.0638***
	(0.008)	(0.008)	(0.011)	(0.011)	(0.013)	(0.013)
(3) - (1)	-0.00317	0.00385	0.0617***	0.0793***	-0.0649***	-0.0755***
	(0.010)	(0.009)	(0.014)	(0.013)	(0.015)	(0.015)
Panel C: Follow trades and hold to day t+20: (0,20)						
(1) Cash account	-0.0145	0.00977	0.0469***	0.0572***	-0.0614***	-0.0474***
	(0.011)	(0.009)	(0.009)	(0.007)	(0.008)	(0.007)
(2) Margin account without experience	-0.0148	0.0133	0.0513***	0.0669***	-0.0661***	-0.0536***
	(0.013)	(0.010)	(0.010)	(0.008)	(0.006)	(0.006)
(3) Margin account with experience	-0.0156	0.0167	0.0599***	0.0839***	-0.0755***	-0.0672***
	(0.015)	(0.011)	(0.013)	(0.010)	(0.006)	(0.006)
(2) - (1)	-0.000289	0.00354	0.00444	0.00973**	-0.00473	-0.00619
	(0.005)	(0.004)	(0.005)	(0.004)	(0.005)	(0.005)
(3) - (2)	-0.000858	0.00341	0.00858	0.0170***	-0.00944	-0.0136**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)
(3) - (1)	-0.00115	0.00695	0.0130	0.0267***	-0.0142*	-0.0197***
	(0.007)	(0.006)	(0.008)	(0.007)	(0.007)	(0.007)

Online Appendix

The online appendix contains the following items:

- Model of Overconfidence and Leveraged Investment
- Investment Literacy Questions from the FINRA Investment Survey
- Financial Literacy Questions from the FINRA State-by-State Survey
- Figure A1. The Trade Performance of Margin and Cash Investors, t=22,42
- Table A1. Overconfidence by Margin Account Availability
- Table A2. Regressions of Margin Account Status on Overconfidence (No Percentile Rank)
- Table A3. Regressions of Margin Experience on Overconfidence (No Percentile Rank)
- Table A4: Counts of Accounts with Large Portfolio Size to Wealth Ratio
- Table A5. Turnover, Speculative Trade, and the Disposition Effect for Cash versus Margin Investors above Median Portfolio Size to Wealth Ratio
- Table A6. Returns from Trading for Cash versus Margin Investors above Median Portfolio Size to Wealth Ratio

Model of Overconfidence and Leveraged Investment

In this section, we develop a model in which investors exhibit possible overconfidence in their understanding of investments and analyze their trading performance as well as their propensity to use margin or leverage. Overconfidence has become a well-established psychological bias in models of financial markets. Our model takes the standard setup of Odean (1998) and others, which captures overconfidence through overestimation of the precision of private information.[1]

Model Setup:

Our theory is a static CARA normal model of trade. There is a riskless asset with zero net return. There is one risky asset with normally-distributed payoff of $\widetilde{v}$ and zero supply. The distribution of $\widetilde{v}$ is given by:

$$\widetilde{v} \sim N(\mu_0, 1/\lambda_0) \tag{1}$$

The assets are exchanged in one round of trading at time $t = 1$, and payoffs are consumed only at $t = 2$. There are N investors of two different types $m\epsilon\{H.L\}$ (high and low information precision). We analyze the limit economy where $N \to \infty$ such that each investor correctly assumes that his own demand does not affect prices. At $t = 0$, each trader has an endowment of f_0 of the riskless asset and of $x_0 = 0$ of the risky asset. Thus, each traders wealth at $t = 0$ is $W_0 = f_0$.

Prior to trading at $t = 1$, each trader, j, receives one of two private signals about the risky asset payoff depending on whether the investor is of type H or L:

$$\widetilde{s}_j = \widetilde{v} + \widetilde{\varepsilon}_m \tag{2}$$

where $\widetilde{\varepsilon}_m$ has the objective distribution $\widetilde{\varepsilon}_m \sim N(0, 1/\lambda_m)$ and $\lambda_H > \lambda_L$ (i.e., type H traders have a higher precision signal than type L). We assume ε_H and ε_L to be independent.

Traders differ not only in the precision of their signals but also in their beliefs about those precisions. Traders believe the distribution of their signal to be $\widetilde{\varepsilon}_m \sim N(0, (\gamma_m\lambda_m)^{-1})$. We refer to γ_m as "confidence" in information. This parameter represents bias in the assessed accuracy of private information about the mean asset payoff. As discussed in Odean (1998), the differing precision of private signals in this model can alternatively be interpreted as differing abilities to interpret public information. The value of $\gamma_m = 1$ represents rational assessment of information accuracy; the values of $\gamma_m > 1$ and $\gamma_m < 1$ represent overconfidence and underconfidence in information, respectively. We focus on the case in which type L investors are systematically moderately overconfident, i.e., $\gamma_L > 1$ and γ_L does not deviate

[1] Other models include Kyle and Wang (1997), Odean (1998), Daniel, Hirshleifer, and Subrahmanyam (1998, 2001), Hirshleifer and Luo (2001), and Hong, Scheinkman, and Xiong (2006)

greatly from one. In this analysis we assume that γ_H is always 1; thus, high information traders are rational while low information traders may be overconfident.

Demand

We assume that agents make inferences about the mean risky asset payoff based upon their signals and do not impute additional information based on the asset's price. This assumption is common in the behavioral asset-pricing literature and is motivated by cognitive limitations on the part of individual investors.[2] Therefore, risky asset demand is based on the payoff distribution conditional on the agent's signal only.

To compute an agent's demand in our CARA-normal setup, we must first specify the agent's perceived mean and variance of the asset payoff conditional on the private signal. The subjective conditional mean payoff of agent j is given as follows (where E'_j is the agent j's subjective expectation):

$$\mu'_j = E'_j[\widetilde{v}|\widetilde{s}_j] = \mu_0 + \left(1 + \frac{\lambda_0}{\gamma_m \lambda_m}\right)^{-1} (\widetilde{s}_j - \mu) = \frac{\lambda_0}{\lambda_0 + \gamma_m \lambda_m}\mu_0 + \frac{\gamma_m \lambda_m}{\lambda_0 + \gamma_m \lambda_m}\widetilde{s}_j \tag{3}$$

This conditional mean is a weighted average of the agent's prior mean payoff and the signal. The weights are determined by the subjective precision of this signal relative to the prior precision of the mean payoff. In particular, higher subjective precision of information results in greater weight on the signal.

The subjective conditional variance of the payoff is given as follows:

$$\begin{aligned} 1/\lambda'_j &= E'_j[(\widetilde{v} - \mu'_j)^2|\widetilde{s}_j] = E'[\left\{\tfrac{\lambda_0}{\lambda_0+\gamma_m\lambda_m}(\widetilde{v} - \mu_0) - \tfrac{\gamma_m\lambda_m}{\lambda_0+\gamma_m\lambda_m}\widetilde{\varepsilon}_m\right\}^2] = \\ &= \left(\tfrac{\lambda_0}{\lambda_0+\gamma_m\lambda_m}\right)^2 \tfrac{1}{\lambda_0} + \left(\tfrac{\gamma_m\hat{\lambda}_m}{\lambda_0+\gamma_m\lambda_m}\right)^2 \tfrac{1}{\gamma_m\lambda_m} = (\lambda_0 + \gamma_m\lambda_m)^{-1} \end{aligned} \tag{4}$$

This is a standard result that posterior precision equals the precision of the prior plus signal precision. Agent j's terminal wealth at time 2 is given by the following equation:

$$W_{2,j} = f_0 + x_{1,j}(\widetilde{v} - p) \tag{5}$$

where $x_{1,j}$ is the number of shares of the risky asset. The agent's (CARA) utility function is $U(W_{2,j}) = -exp(-rW_{2,j})$, where r is the coefficient of absolute risk-aversion, assumed, for simplicity, to be equal across agents. We apply a monotonic transform to the agent's expected utility to obtain the following objective function:

$$\max_{x_{1,j}} \left\{ -\frac{1}{r} \log\left(-E'[U(W_{2,j})|\widetilde{s}_j]\right) = f_0 + x_{1,j}(\mu'_j - p) - \frac{r}{2\lambda'_j} x_{1,j}^2 \right\} \tag{6}$$

The first-order condition for $x_{1,j}$ yields the solution:

$$\begin{aligned} x^*_{1,j}(\widetilde{s}_j, P_1) &= r^{-1}(\lambda_0 + \gamma_m\lambda_m)\left[\tfrac{\lambda_0}{\lambda_0+\gamma_m\lambda_m}\mu_0 + \tfrac{\gamma_m\lambda_m}{\lambda_0+\gamma_m\lambda_m}\widetilde{s}_j - P_1\right] \\ &= r^{-1}[\lambda_0\mu_0 + \gamma_m\lambda_m\widetilde{s}_j - (\lambda_0 + \gamma_m\lambda_m)P_1] \end{aligned} \tag{7}$$

[2]See Eyster, Rabin, and Vayanos (2018) and the references contained therein.

Pricing and Volume

Aggregate equilibrium demand for the risky asset is equal to the sum of demand across traders given by:

$$\begin{aligned}&\textstyle\sum_{j\epsilon\mathcal{H}} x_{1,j}^*(\widetilde{s}_j, P_1) + \sum_{k\epsilon\mathcal{L}} x_{1,k}^*(\widetilde{s}_k, P_1) \\ &= \tfrac{N}{2} r^{-1}\left[2\lambda_0\mu_0 + (\gamma_H\lambda_H + \gamma_L\lambda_L)\widetilde{v} + \gamma_H\lambda_H\widetilde{\varepsilon}_H + \gamma_L\lambda_L\widetilde{\varepsilon}_L - (2\lambda_0 + \gamma_H\lambda_H + \gamma_L\lambda_L)P_1\right]\end{aligned} \tag{8}$$

where $\mathcal{H}$ and $\mathcal{L}$ denote the set of indexes for high information and low information type traders, respectively. In equilibrium, this demand equals the supply of zero. Therefore, the equilibrium price of the risky asset is given by:

$$\begin{aligned}P_1^* &= (2\lambda_0 + \gamma_H\lambda_H + \gamma_L\lambda_L)^{-1}\left[2\lambda_0\mu_0 + (\gamma_H\lambda_H + \gamma_L\lambda_L)\widetilde{v} + \gamma_H\lambda_H\widetilde{\varepsilon}_H + \gamma_L\lambda_L\widetilde{\varepsilon}_L\right] \\ &= \mu_0 + (2\lambda_0 + \gamma_H\lambda_H + \gamma_L\lambda_L)^{-1}\left[(\gamma_H\lambda_H + \gamma_L\lambda_L)(\widetilde{v} - \mu_0) + \gamma_H\lambda_H\widetilde{\varepsilon}_H + \gamma_L\lambda_L\widetilde{\varepsilon}_L\right]\end{aligned} \tag{9}$$

We represent a trader's trading volume (in shares) as the variance of demand in equilibrium. Substituting equation 9 into 7, we obtain the following expression for the equilibrium demand of a type L trader j:

$$x_{1,j}^*(\widetilde{s}_j, P_1^*) = \frac{\lambda_0(\gamma_L\lambda_L - \gamma_H\lambda_H)(\widetilde{v} - \mu_0) + \gamma_L\lambda_L(\lambda_0 + \gamma_H\lambda_H)\widetilde{\varepsilon}_L - \gamma_H\lambda_H(\lambda_0 + \gamma_L\lambda_L)\widetilde{\varepsilon}_H}{r(2\lambda_0 + \gamma_H\lambda_H + \gamma_L\lambda_L)} \tag{10}$$

Therefore, the variance of this demand is given as follows:

$$var(x_{1,j}^*(\widetilde{s}_j, P_1^*)) = \frac{\lambda_0(\gamma_L\lambda_L - \gamma_H\lambda_H)^2 + \gamma_L^2\lambda_L(\lambda_0 + \gamma_H\lambda_H)^2 + \gamma_H^2\lambda_H(\lambda_0 + \gamma_L\lambda_L)^2}{r^2(2\lambda_0 + \gamma_H\lambda_H + \gamma_L\lambda_L)^2} \tag{11}$$

The trading volume of a trader of type H is identical except with H and L switched in this equation. The following propositions are straightforward from this expression:

Proposition 1

a. *Low information traders' trading volume increases in overconfidence.*

b. *Low information traders' trading volume increases in signal precision if* $\gamma_L \leq 2$.

Proof:

The partial derivative of the variance of demand for type L traders with respect to overconfidence is given by:

$$\begin{aligned}&\tfrac{\partial var(x_{1,j}^*(\widetilde{s}_j, P_1^*))}{\partial\gamma_L} = \\ &= 2\lambda_L(\lambda_0 + \gamma_H\lambda_H)\tfrac{2\lambda_0\gamma_L(\lambda_0+\lambda_L)+\gamma_H\lambda_H[\gamma_L\lambda_L\gamma_H+\lambda_0(3\gamma_L+\gamma_H-2)]+\gamma_L\gamma_H^2\lambda_H^2}{r^2(2\lambda_0+\gamma_H\lambda_H+\gamma_L\lambda_L)^3}\end{aligned} \tag{12}$$

It is clear that this expression is positive for γ_L, $\gamma_H \geq 1$. The partial derivative with respect to signal precision is given by:

$$\begin{aligned}&\tfrac{\partial var(x_{1,j}^*(\widetilde{s}_j, P_1^*))}{\partial\lambda_L} = \\ &= \gamma_L(\lambda_0 + \gamma_H\lambda_H)\tfrac{\lambda_0[2(\gamma_H-2)+3\gamma_L]\gamma_H\lambda_H+\lambda_0(4-\gamma_L)\gamma_L\lambda_L+(2\gamma_H-\gamma_L)\gamma_L\lambda_L\gamma_H\lambda_H+\gamma_L(2\lambda_0^2+\gamma_H^2\lambda_H^2)}{r^2(2\lambda_0+\gamma_H\lambda_H+\gamma_L\lambda_L)^3}\end{aligned} \tag{13}$$

It is clear that this expression is positive for $\gamma_H = 1$ and $\gamma_L\epsilon[1, 2]$. QED.

Profit

We now analyze trading profits as a function of overconfidence and information precision. Trader j's equilibrium profit from trading the risky asset is given by the following expression:

$$\Pi_j^* = x_{1,j}^*(\widetilde{s}_j, P_1^*)(\widetilde{v} - P_1^*) \tag{14}$$

For a trader of type L, this profit can be rewritten as follows:

$$\begin{aligned}\Pi_L^* &= r^{-1}(2\lambda_0 + \gamma_H\lambda_H + \gamma_L\lambda_L)^{-2}\left[2\lambda_0(\widetilde{v} - \mu_0) - \gamma_H\lambda_H\widetilde{\varepsilon}_H - \gamma_L\lambda_L\widetilde{\varepsilon}_L\right] \cdot \\ &\cdot \left[\lambda_0(\gamma_L\lambda_L - \gamma_H\lambda_H)(\widetilde{v} - \mu_0) + \gamma_L\lambda_L(\lambda_0 + \gamma_H\lambda_H)\widetilde{\varepsilon}_L - \gamma_H\lambda_H(\lambda_0 + \gamma_L\lambda_L)\widetilde{\varepsilon}_H\right]\end{aligned} \tag{15}$$

Therefore, the objective expected profit of a trader of type L is given by the following equation:

$$E[\Pi_L^*] = \frac{2\lambda_0(\gamma_L\lambda_L - \gamma_H\lambda_H) - \gamma_L^2\lambda_L(\lambda_0 + \gamma_H\lambda_H) + \gamma_H^2\lambda_H(\lambda_0 + \gamma_L\lambda_L)}{r(2\lambda_0 + \gamma_H\lambda_H + \gamma_L\lambda_L)^2} \tag{16}$$

The expected profit of a trader of type H is again identical except with H and L switched in this equation. The following propositions are straightforward from this expression:

Proposition 2

a. *Low information traders' expected profit decreases in overconfidence.*

b. *Low information traders' expected profit increases in signal precision for $\gamma_L = 1$.*

Proof:

The partial derivative of the expected profit of type L traders with respect to overconfidence is given by:

$$\begin{aligned}&\frac{\partial E[\Pi_L^*]}{\partial \gamma_L} = \\ &= \lambda_L \frac{-4\lambda_0^2(\gamma_L - 1) + 6\lambda_0\gamma_H\lambda_H - 2\lambda_0\gamma_L(\lambda_L + 3\gamma_H\lambda_H) + \gamma_H^2\lambda_H[\gamma_H\lambda_H - \gamma_L(\lambda_L + 2\lambda_H)]}{r(2\lambda_0 + \gamma_H\lambda_H + \gamma_L\lambda_L)^3}\Bigg|_{\gamma_H = 1} \\ &= \lambda_L \frac{-4\lambda_0^2(\gamma_L - 1) - 2\lambda_0[\gamma_L\lambda_L + 3(\gamma_L - 1)\lambda_H] - \lambda_H[\gamma_L\lambda_L + (2\gamma_L - 1)\lambda_H]}{r(2\lambda_0 + \lambda_H + \gamma_L\lambda_L)^3}\end{aligned} \tag{17}$$

It is clear that this final expression is positive for $\gamma_L > 1$. The partial derivative of the expected profit of type L traders with respect to signal precision is given by:

$$\begin{aligned}&\frac{\partial E[\Pi_L^*]}{\partial \lambda_L} = \\ &= \gamma_L \frac{-2\lambda_0^2(\gamma_L - 2) + \lambda_0(\gamma_L - 2)(\gamma_L\lambda_L - 3\gamma_H\lambda_H) + (\gamma_L - \gamma_H)(\gamma_L\lambda_L - \gamma_H\lambda_H)\gamma_H\lambda_H}{r(2\lambda_0 + \gamma_H\lambda_H + \gamma_L\lambda_L)^3}\Bigg|_{\gamma_L, \gamma_H = 1} \\ &= \frac{2\lambda_0^2 - \lambda_0(\lambda_L - 3\lambda_H)}{r(2\lambda_0 + \lambda_H + \lambda_L)^3}\end{aligned} \tag{18}$$

It is clear that this final expression is positive since $\lambda_H > \lambda_L$.

Margin

We define the propensity for using margin or leverage as the probability of dollar risky asset demand exceeding wealth.[3] To simplify the analysis that follows, we assume that $\mu_0 \gg \gamma_L/\lambda_0$. This inequality is true if: 1.) the chance of the risky asset payoff being zero (or below) is low and 2.) γ_L is sufficiently low. Under this assumption, the equilibrium price is approximately equal to $P_1^* \approx \mu_0$ from equation 9. Therefore, dollar demand is approximately equal to the following expression according to equation 10:

$$\begin{aligned}&P_1^* x_{1,j}^*(\widetilde{s}_j, P_1^*) \approx \mu_0 x_{1,j}^*(\widetilde{s}_j, P_1^*)\\ &= \tfrac{\mu_0}{r} \cdot \tfrac{\lambda_0(\gamma_L\lambda_L - \gamma_H\lambda_H)(\widetilde{v}-\mu_0) + \gamma_L\lambda_L(\lambda_0+\gamma_H\lambda_H)\widetilde{\varepsilon}_L - \gamma_H\lambda_H(\lambda_0+\gamma_L\lambda_L)\widetilde{\varepsilon}_H}{2\lambda_0+\gamma_L\lambda_L+\gamma_H\lambda_H}\end{aligned} \tag{19}$$

Therefore, dollar demand has a distribution that is approximately normal such that the probability of margin use is given as follows:

$$\mathcal{M} \approx 1 - \Phi\left(\frac{W_0 - E[P_1^* x_{1,j}^*(\widetilde{s}_j, P_1^*)]}{var(P_1^* x_{1,j}^*(\widetilde{s}_j, P_1^*))^{1/2}}\right) \tag{20}$$

It is clear from equation 20 that $\mathcal{M}$ is increasing in expected demand and the variance of demand since the standard normal CDF, Φ, is an increasing function. Intuitively, increasing either the expectation or the variance of demand increases the right tail of the distribution for demand, thereby increasing the chance of taking a position that exceeds wealth. The following proposition describes the comparative statics of margin use as a function of confidence:

Proposition 3 *If $\mu_0 \gg \gamma_L/\lambda_0$, the following two properties hold:*

a. *Low information traders' probability of margin use increases in overconfidence.*

b. *Low information traders' probability of margin use increases in signal precision if $\gamma_L \leq 2$.*

Proof:

From equation 19, expected dollar demand is approximately to zero. The variance of dollar demand is approximately equal to μ_0 times the variance of share demand, i.e.:

$$var(P_1^* x_{1,j}^*(\widetilde{s}_j, P_1^*)) \approx \mu_0^2 var(x_{1,j}^*(\widetilde{s}_j, P_1^*)) \tag{21}$$

Since the variance of share demand is increasing in γ_L by proposition 1, the probability of margin use in equation 20 also increases in γ_L. By the same argument, proposition 1 also implies that the probability of margin use increases in λ_L for $\gamma_L \leq 2$. QED.

[3] In this context, wealth (W_0) represents the amount potentially allocated to investment accounts such that the investor will borrow if they seek to invest more than this amount. This "wealth" will be less than household net worth in general as certain assets may be illiquid or earmarked for other accounts and purposes.

Investment Literacy Questions from the FINRA Investment Survey

1. If you buy a company's stock...
   - You own a part of the company
   - You have lent money to the company
   - You are liable for the company's debts
   - The company will return your original investment to you with
2. If you buy a company's bond...
   - You own a part of the company
   - You have lent money to the company
   - You are liable for the company's debts
   - You can vote on shareholder resolutions
3. If a company files for bankruptcy, which of the following securities is most at risk of becoming virtually worthless?
   - The company's preferred stock
   - The company's common stock
   - The company's bonds
4. In general, investments that are riskier tend to provide higher returns over time than investments with less risk.
   - True
   - False
5. Over the last 20 years in the US, the best average returns have been generated by:
   - Stocks
   - Bonds
   - CDs
   - Money market accounts
   - Precious metals
6. What has been the approximate average annual return of the S&P 500 stock index over the past 20 years (not adjusted for inflation)?
   - -10%
   - -5%
   - +5%
   - +10%
   - +15%
   - +20%
7. Which of the following best explains the distinction between nominal returns and real returns?
   - Nominal returns are pre-tax returns; real returns are after
   - Nominal returns are what an investment is expected to earn;
   - Nominal returns are not adjusted for inflation; real return
   - Nominal returns are not adjusted for fees and expenses; real
8. Which of the following best explains why many municipal bonds pay lower yields than other government bonds?
   - Municipal bonds are lower risk
   - There is a greater demand for municipal bonds
   - Municipal bonds can be tax-free
9. You invest $500 to buy $1,000 worth of stock on margin. The value of the stock drops by 50%. You sell it. Approximately how much of your original $500 investment are you left with in the end?
   - $500
   - $250
   - $0
10. Which is the best definition of 'selling short?'
    - Selling shares of a stock shortly after buying it
    - Selling shares of a stock before it has reached its peak
    - Selling shares of a stock at a loss
    - Selling borrowed shares of a stock

Financial Literacy Questions from the FINRA State-by-State Survey

1. Suppose you had $100 in a savings account and the interest rate was 2% per year. After 5 years, how much do you think you would have in the account if you left the money to grow?
    - <u>More than $102</u>
    - Exactly $102
    - Less than $102
2. Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, how much would you be able to buy with the money in this account?
    - More than today
    - Exactly the same
    - <u>Less than today</u>
3. If interest rates rise, what will typically happen to bond prices?
    - They will rise
    - <u>They will fall</u>
    - They will stay the same
    - There is no relationship between bond prices and the interest.
4. Suppose you owe $1,000 on a loan and the interest rate you are charged is 20% per year compounded annually. If you didn't pay anything off, at this interest rate, how many years would it take for the amount you owe to double?
    - Less than 2 years
    - <u>At least 2 years but less than 5 years</u>
    - At least 5 years but
5. A 15-year mortgage typically requires higher monthly payments than a 30-year mortgage, but the total interest paid over the life of the loan will be less.
    - <u>True</u>
    - False
6. Buying a single company's stock usually provides a safer return than a stock mutual fund.
    - True
    - <u>False</u>

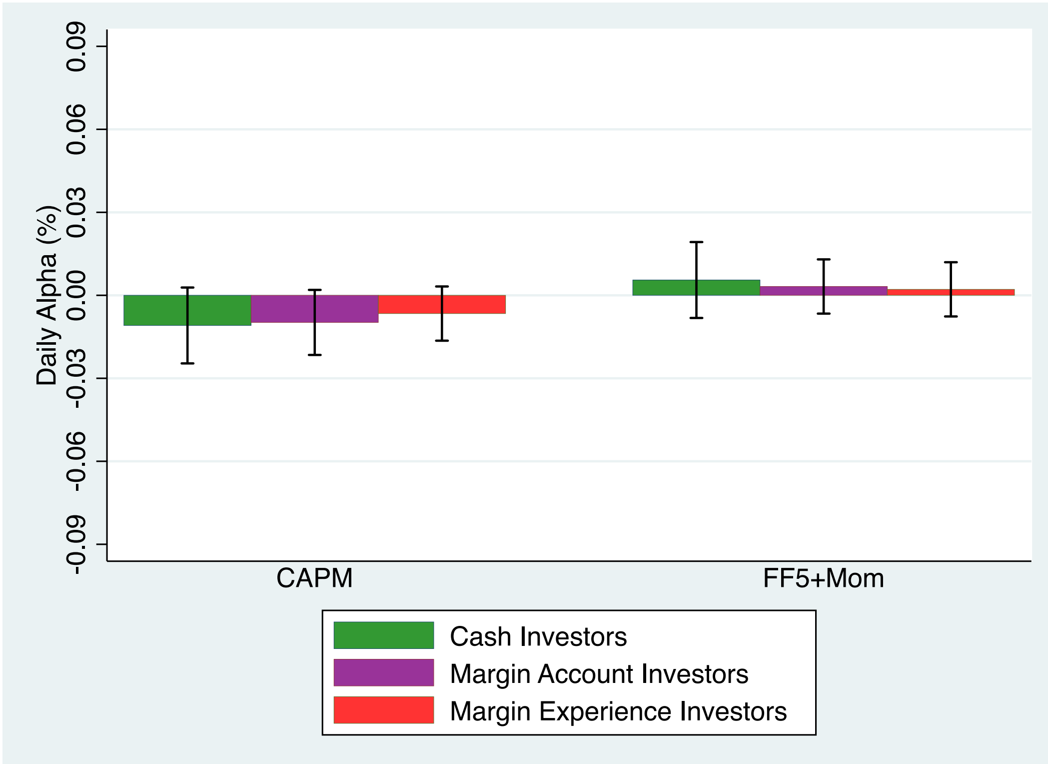


Figure A1. The Trade Performance of Margin and Cash Investors, t=22,42
The bars present the daily percentage alpha on a long-short portfolio that mimics the trades three investor groups and sells positions at market close three days after the trade, *t=22,42* . Cash investors trade only in cash accounts. Margin account investors hold margin accounts but we do not observe short positions or options trades in their accounts. Margin experience investors are investors with margin accounts and experience trading options or shorting. The long portfolio that mimics the buys of an investor group; the short portfolio mimics the sells. The daily percentage abnormal return (or alpha) on the portfolio is measured as the intercept from a regression of the portfolio excess return on the market excess return (CAPM alpha) or the portfolio excess return on the Fama-French five-factor model plus momentum (FF5+Mom). The trades data are from a discount broker. Whiskers depict 95% confidence intervals.

Table A1: Overconfidence by Margin Account Availability

The table presents mean values of overconfidence variables (and its components) by each household's answer to the Margin Account question (Yes, No, DNK- do not know). Overconfidence in financial literacy is the percentile rank on a person's self-assessment of financial knowledge less the percentile rank on a person's score on a six question financial literacy quiz (OC_fin = finself_p - finlit_p). Overconfidence in investment literacy is the difference between the percentile rank on a person's self-assessment of investment knowledge less the percentile rank on a person's score on a ten question financial literacy quiz (OC_inv = invself_p - invlit_p). Overconfidence in performance is a dummy variable that takes a value of one if the respondents expected to perform better than the market (OC_perf).

	N	Mean	Mean	Mean	Mean	Mean
Panel A: Overconfidence in Financial Literacy, OC_fin = finself_p - finlit_p						
		OC fin	*finself p*	*finlit p*	*finself*	*finlit*
Yes	595	0.131	0.613	0.482	6.153	0.683
No	504	-0.089	0.516	0.605	5.845	0.795
DNK	502	-0.065	0.433	0.497	5.568	0.716
Yes - No		0.220***	0.097***	-0.123***	0.308***	-0.112***
		(0.023)	(0.016)	(0.017)	(0.050)	(0.015)
Yes - DNK		0.196***	0.180***	-0.015	0.585***	-0.033**
		(0.023)	(0.015)	(0.017)	(0.051)	(0.015)
No - DNK		-0.024	0.083***	0.108***	0.277***	0.079***
		(0.022)	(0.017)	(0.016)	(0.055)	(0.013)
Panel B: Overconfidence in Investment Literacy, OC_inv = invself_p - invlit_p						
		OC inv	*invself p*	*invlit p*	*invself*	*invlit*
Yes	595	0.137	0.687	0.549	5.748	0.511
No	504	-0.090	0.510	0.600	4.942	0.539
DNK	502	-0.076	0.392	0.468	4.369	0.440
Yes - No		0.227***	0.177***	-0.051***	0.806***	-0.028**
		(0.022)	(0.015)	(0.017)	(0.067)	(0.013)
Yes - DNK		0.213***	0.295***	0.081***	1.379***	0.071***
		(0.022)	(0.014)	(0.017)	(0.069)	(0.013)
No - DNK		-0.014	0.118***	0.132***	0.573***	0.099***
		(0.020)	(0.016)	(0.017)	(0.076)	(0.013)
Panel C: Overconfidence in Performance, OC_perf						
Yes	595	0.390				
No	504	0.248				
DNK	502	0.197				
Yes - No		0.142***				
		(0.028)				
Yes - DNK		0.193***				
		(0.027)				
No - DNK		0.051*				
		(0.026)				

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A2. Regressions of Margin Account Status on Overconfidence (No Percentile Rank)

The table presents linear probability models where the dependent variable is a dummy variable that takes a value of one if the household has margin account and zero for households without margin or do not know. The key independent variables are Overconfidence in Investment Literacy (Panel A), Financial Literacy (Panel B), and Performance (Panel C). Overconfidence in investment literacy is the difference between a person's self-assessment of investment knowledge (invself) less the person's score on a ten question financial literacy quiz (invlit). Overconfidence in financial literacy is the difference between the person's self-assessment of financial knowledge (finself) less the person's score on a six question financial literacy quiz (finlit). Panel D lists control variables. Demographic controls include dummy variables for college education, nonwhite, gender, marital status, presence of children, age bins (<35, 35-54, >54), portolio size bins (<$50k, $50-$250k, >$250k). Preference controls include dummy variables for willingness to take risks (none, average, above average, high), stock allocation in portfolio (none, <=50%, >50%), trust in markets (10 point Likert scale), and trust in regulation (10 point Likert scale).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Overconfidence in Investment Literacy, OC_invlit = invself - invlit								
OC_invlit	0.463***	0.321***	0.264***	0.232***	1.079***	0.813***	0.739***	0.620***
	(0.045)	(0.047)	(0.050)	(0.050)	(0.054)	(0.059)	(0.066)	(0.066)
invlit_perc					1.042***	0.858***	0.730***	0.633***
					(0.069)	(0.076)	(0.075)	(0.079)
Observations	1,601	1,601	1,601	1,601	1,601	1,601	1,601	1,601
R-squared	0.062	0.178	0.189	0.244	0.168	0.238	0.232	0.272
Panel B: Overconfidence in Financial Literacy, OC_finlit = finself - finlit								
OC_finlit	0.442***	0.332***	0.259***	0.250***	0.936***	0.751***	0.561***	0.510***
	(0.042)	(0.042)	(0.043)	(0.043)	(0.086)	(0.087)	(0.090)	(0.091)
finlit_perc					0.635***	0.565***	0.384***	0.344***
					(0.102)	(0.105)	(0.102)	(0.106)
Observations	1,601	1,601	1,601	1,601	1,601	1,601	1,601	1,601
R-squared	0.060	0.183	0.190	0.247	0.081	0.198	0.197	0.253
Panel C: Overconfidence in Performance, OC_perf (Expected to Outperform Stock Market)								
OC_perf	0.192***	0.129***	0.097***	0.073***	--	--	--	--
	(0.027)	(0.026)	(0.027)	(0.026)	--	--	--	--
Observations	1,601	1,601	1,601	1,601	--	--	--	--
R-squared	0.032	0.168	0.181	0.238	--	--	--	--
Panel D: Control Variables								
Demographic	NO	YES	NO	YES	NO	YES	NO	YES
Risk and Trust	NO	NO	YES	YES	NO	NO	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table A3. Regressions of Margin Experience on Overconfidence (No Percentile Rank)

The table presents linear probability models where the dependent variable is a dummy variable that takes a value of one if the household has used margin and zero if the household has not; the sample consists of households with a margin account. Households with cash accounts are excluded. The key independent variables are Overconfidence in Investment Literacy (Panel A), Financial Literacy (Panel B), and Performance (Panel C). Overconfidence in investment literacy is the difference between a person's self-assessment of investment knowledge (invself) less the person's score on a ten question financial literacy quiz (invlit). Overconfidence in financial literacy is the difference between a person's self-assessment of financial knowledge (finself) less the percentile rank on a person's score on a six question financial literacy quiz (finlit). Panel D lists control variables. Demographic controls include dummy variables for college education, nonwhite, gender, marital status, presence of children, age bins (<35, 35-54, >54), portolio size bins (<$50k, $50-$250k, >$250k). Preference controls include dummy variables for willingness to take risks (none, average, above average, high), stock allocation in portfolio (none, <=50%, >50%), trust in markets (10 point Likert scale), and trust in regulation (10 point Likert scale).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Overconfidence in Investment Literacy, OC_invlit = invself - invlit								
OC_invlit	0.669***	0.474***	0.388***	0.342***	1.044***	0.807***	0.556***	0.520***
	(0.066)	(0.082)	(0.080)	(0.087)	(0.133)	(0.142)	(0.142)	(0.146)
invlit_perc					0.550***	0.522***	0.232	0.264
					(0.171)	(0.178)	(0.162)	(0.174)
Observations	595	595	595	595	595	595	595	595
R-squared	0.140	0.208	0.276	0.295	0.158	0.222	0.279	0.298
Panel B: Overconfidence in Financial Literacy, OC_finlit = finself - finlit								
OC_finlit	0.588***	0.409***	0.259***	0.227***	0.441**	0.394**	0.036	0.094
	(0.061)	(0.073)	(0.081)	(0.084)	(0.171)	(0.168)	(0.172)	(0.174)
finlit_perc					-0.177	-0.018	-0.269	-0.165
					(0.195)	(0.199)	(0.185)	(0.194)
Observations	595	595	595	595	595	595	595	595
R-squared	0.127	0.205	0.260	0.284	0.128	0.205	0.263	0.285
Panel C: Overconfidence in Performance, OC_perf (Expected to Outperform Stock Market)								
OC_perf	0.145***	0.109***	0.092**	0.086**	--	--	--	--
	(0.042)	(0.039)	(0.037)	(0.037)	--	--	--	--
Observations	595	595	595	595	--	--	--	--
R-squared	0.020	0.170	0.252	0.280	--	--	--	--
Panel D: Control Variables								
Demographic	NO	YES	NO	YES	NO	YES	NO	YES
Risk and Trust	NO	NO	YES	YES	NO	NO	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table A4: Counts of Accounts with Large Portfolio Size to Wealth Ratio

The median portfolio size to wealth ratio is 17.7%. The table presents the count of accounts with above/below median wealth ratio by account type (cash, margin account/no experience, margin experience).

	Portfolio size/ wealth ratio			Portfolio size/ wealth ratio		
	below median	above median	Total	below median	above median	Total
cash	3,255	2,177	5,432	59.9%	40.1%	100.0%
marginacc	4,580	5,060	9,640	47.5%	52.5%	100.0%
marginexp	991	1,557	2,548	38.9%	61.1%	100.0%
Total	8,826	8,794	17,620	50.1%	49.9%	100.0%

Table A5. Turnover, Speculative Trade, and the Disposition Effect for Cash versus Margin Investors

The sample are households above the median ratio of portfolio size to wealth (17.7%). The unit of observation is household. The dependent variable is either mean monthly turnover (turnover in columns 1-2), proportion of trades that are speculative (columns 3-4), or the ratio of PGR to PLR (*PGRtoPLR* of columns 5-6). The key independent variables are *marginacc* , which equals one if the household has margin accounts, and *marginexp* , which equals one if the household has experience trading options or shorting stock. In the regressions without controls (columns 1, 3, and 5), the intercept can be interpreted as the mean value of the dependent variable for cash investors. Investor controls include variables from Table 3, Panel C (man, age, married, child_dum, knowledge, experience, income, wealth). In columns 2, 4, and 6, for each variable observations with missing data are assigned the mean value for the variable and a missing dummy variable equals one. Robust standard errors are in parentheses. ***, **, * significant at the 1%, 5%, 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep var:	*turnover*		*spec_trade*		*PGRtoPLR*	
cash (Intercept)	0.0664***	n.a.	0.182***	n.a.	1.915***	n.a.
	(0.002)		(0.005)		(0.057)	
marginacc	0.00907***	0.00955***	0.0150**	0.0119*	0.0960	0.0865
	(0.003)	(0.003)	(0.006)	(0.006)	(0.076)	(0.081)
marginexp	0.0679***	0.0662***	0.132***	0.126***	0.365***	0.329***
	(0.004)	(0.004)	(0.007)	(0.007)	(0.084)	(0.082)
Investor Controls	No	Yes	No	Yes	No	Yes
Observations	8003	8003	8003	8003	4496	4496
R-squared	0.051	0.067	0.051	0.064	0.006	0.026

Table A6. Returns from Trading for Cash versus Margin Investors

The sample are households above the median ratio of portfolio size to wealth (17.7%). The unit of observation is trade. The dependent variable is the return following a trade (the return on the traded stock minus a value-weighted market index). The key independent variables are *marginacc* , which equals one if the household has margin accounts, and *marginexp* , which equals one if the household has experience trading options or shorting stock. In the regressions without controls, the intercept can be interpreted as the mean return earned on trades in cash accounts. Investor controls include variables from Table 3, Panel C (*man* , *age* , *married* , *child_dum* , *knowledge* , *experience* , *income* , *wealth*); for each variable, observations with missing data are assigned the mean value for the variable and a missing dummy variable equals one. Standard errors are clustered by trading date and are robust to heteroscedasticity. Standard errors are in parentheses. ***, **, * significant at the 1%, 5%, 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Returns following Buys						
Dep. Var.:	$R^b(0,3)$		$R^b(0,5)$		$R^b(0,20)$	
cash (Intercept)	-0.429***	n.a.	-0.440***	n.a.	-0.541***	n.a.
	(0.060)		(0.070)		(0.126)	
marginacc	0.0749	0.0985*	0.0488	0.0550	0.0627	0.0940
	(0.055)	(0.057)	(0.065)	(0.067)	(0.111)	(0.112)
marginexp	-0.0495	-0.0672	-0.0186	-0.0437	-0.0599	-0.0739
	(0.048)	(0.048)	(0.054)	(0.055)	(0.092)	(0.096)
Investor Controls	209237	209237	209237	209237	209237	209237
Observations	0.000	0.002	0.000	0.002	0.000	0.001
Panel B: Returns following Sales						
Dep. Var.:	$R^s(0,3)$		$R^s(0,5)$		$R^s(0,20)$	
cash (Intercept)	0.597***	n.a.	0.586***	n.a.	0.901***	n.a.
	(0.065)		(0.077)		(0.152)	
marginacc	0.159**	0.152**	0.238***	0.234***	0.201	0.218
	(0.064)	(0.068)	(0.074)	(0.077)	(0.141)	(0.147)
marginexp	0.387***	0.368***	0.297***	0.297***	0.0659	0.128
	(0.082)	(0.080)	(0.087)	(0.084)	(0.121)	(0.119)
Investor Controls	174624	174624	174624	174624	174624	174624
Observations	0.001	0.002	0.000	0.002	0.000	0.001