

ORIGINAL RESEARCH

The Impact Of Overestimation On US Trading Patterns And Diversification Of Portfolio Holdings

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Abstract

This paper examines whether US households that overestimate their financial knowledge trade more actively and hold less diversified portfolios. Using microdata from the 2022 Survey of Consumer Finances, a nationally representative sample of 4,595 US households, an overconfidence gap is constructed by subtracting the z-scored financial literacy score (FINLIT) from the z-scored self-rated financial knowledge score (KNOWL). OLS regression models are estimated separately across five imputed datasets and combined using Rubin's rules. Results consistently support the first hypothesis: a one-unit increase in the overconfidence gap is associated with a 12.3% increase in trading activity among brokerage-account holders, robust to demographic, wealth, and risk controls. The second hypothesis is not supported; more overconfident households hold significantly more (1.52 unique stocks) rather than fewer distinct stocks. This finding is interpreted as reflecting a higher willingness to participate in individual equity markets rather than true risk-reducing portfolio diversification. These findings extend prior literature by testing overconfidence within a representative population sample rather than single-brokerage customer data, and suggest that policy aimed at improving financial self-calibration, not just financial knowledge, may reduce the welfare costs of overconfident investing.

Keywords: Overconfidence; Portfolio Diversification; Financial Knowledge; Behavioral Finance; Trading

JEL: G41, G11, D91, G12, G14

1. Introduction

1.1 Background and Motivation

In January 2021, a wave of retail investors contributed to a surge in the share price of GameStop, a struggling video game retailer, up by more than 1,600% in a matter of weeks. This turned a stock that had traded under \$10 into one closing near \$328 (Iacurci, 2026). Many of these investors, often trading through commission-free apps for the first time, acted under the belief that they could outmaneuver professional fund managers, reflecting behavioural biases such as overconfidence and an illusion of informational advantage. Iacurci also found that the median investor who bought in after the rally had already lost roughly 13% of their investment. This indicated that confidence in their trading ability did not necessarily translate into superior returns. Behavioral finance defines overconfidence as investors'

tendency to overestimate the accuracy of their judgments, knowledge, and forecasting abilities (Daniel & Hirshleifer, 2015; Barber & Odean, 2000). This single episode captures, in dramatic and highly visible form, a pattern that has been documented across financial markets for decades and across very different contexts: investors who believe too strongly in the accuracy of their own judgment, the quality of their information, or their ability to time the market, tend to trade more frequently, diversify less, take on more risk than is prudent (Barber & Odean, 2000; Odean, 1999), and ultimately earn lower returns than those who invest more cautiously and less actively.

The GameStop episode is an illustration of far costlier phenomenon that extends well beyond any single stock or trading event. According to DALBAR, which analyses investor behavior, the average US equity fund investor earned just 16.54% in 2024, compared to the S&P 500's 25.05% return that same year. This led to a shortfall of 848 basis points (DALBAR, 2025; Ferreira & Felipe, 2026, pp.12) and one of the largest performance gaps the firm has recorded in three decades of tracking investor behavior. What do these two figures actually measure? The S&P 500 return represents what any investor would have earned by simply buying and holding a low-cost index fund that passively tracks the 500 largest publicly listed US companies, making no active decisions whatsoever (DALBAR, 2025). A US equity fund investor, by contrast, is someone who actively buys and sells funds in response to market movements, news, or personal judgment about where the market is heading (Barber & Odean, 2000).

The gap between these two figures therefore does not reflect differences in available investments, since both access the same market. It reflects the cost of the active decisions themselves: buying too late after markets have risen, selling too early during downturns, and missing recoveries by sitting on the sidelines. This gap is a concern precisely because it is avoidable. The S&P 500 return is freely accessible to any investor through a passive index fund, meaning the 848 basis point shortfall represents wealth that ordinary investors are leaving on the table, year after year, as a direct result of behavioral patterns. DALBAR attributes much of this underperformance to behavioral patterns such as withdrawing funds during downturns and only re-entering markets after gains have already occurred, missing much of the recovery in the process. These behaviors are often linked to overconfidence, whereby investors believe they can successfully predict market turning points. As retail trading has become more accessible through mobile apps and more visible through social media (Amundi Institute, 2023), the consequences of these individual decisions are increasingly reflected through prices, trading volume, and the overall efficiency of markets.

1.2 Research Question

Do U.S. households that overestimate their own financial knowledge trade more actively and hold less diversified portfolios?

1.3 Contribution of the Paper

This paper adds to the existing research on overconfidence and investing in three main ways. First, it uses a dataset that most studies do not have access to, one that asks the same people both how confident they feel about their financial knowledge and then actually tests that knowledge with real questions including about both their self-assessed financial knowledge and willingness to take financial risk. This means the gap between what people think they know and what they actually know can be measured directly, rather than being estimated indirectly from trading records alone. Most existing studies use data from a single brokerage firm or a small group of participants, so the findings from this paper are more likely to apply to ordinary American households in general. Second, the paper handles a technical problem that many similar studies ignore, which is that the Survey of Consumer Finance (SCF hereafter), gives five slightly different versions of each household's data rather than one. This paper deals using Rubin's rules, which corrects the artificially small standard errors that result from treating the five implicates as independent observations. Third, the paper responds to a specific gap in the literature pointed out by Singh, et al. (2024), who found that researchers have spent a lot of time studying what causes overconfidence but not enough time studying what overconfident investors actually do differently. This paper focuses on exactly that question.

1.4 Structure of the Paper

Subsequently, Section 2 reviews the existing academic research on overconfidence, financial literacy, investment behavior, and explains what gap this paper is trying to fill. Section 3 describes the dataset used, including the most important variables, and its limitations. Section 4 explains the methodology, what the two hypotheses are, and presents the regression models. Section 5 presents the results, discusses what policy implications they might have, and connects them back to the studies reviewed in Section 2. Section 6 concludes by summarizing the main findings and suggesting directions for future research. Section 7 contains the full bibliography.

2. Literature Review

This section will cover relevant papers that align with the research question, alongside discussing relevant theoretical concepts while also highlighting the gaps in the literature.

2.1 Key Concepts and Theories

Several interconnected concepts from behavioral finance underpin this paper's framework. Overconfidence takes multiple forms: miscalibration (overestimating the precision of one's information), the better-than-average effect (believing oneself to be more skilled than peers), and illusion of control (believing one can influence outcomes that are in fact random) (Odean, 1998). The first two matter most for investment decisions, leading investors to underestimate risk, over-trade, and hold concentrated portfolios (Odean, 1998; Barber et al. 2000). Closely related is financial literacy, the objective knowledge required for sound financial decisions. The gap between self-assessed financial knowledge and objectively measured financial literacy, the "overconfidence gap," is now a widely used empirical measure of investor overconfidence (Lusardi & Mitchell, 2014), and forms the basis of the overconfidence measure used here. Loss aversion, formalized by Kahneman et al. (1979), describes investors feeling losses more acutely than equivalent gains, producing asymmetric risk-taking behavior. The disposition effect, selling winning stocks too early and holding losing stocks too long, follows directly from loss aversion and, as Gödker et al. (2025) show, further reinforces overconfidence by distorting the information investors use to evaluate their own ability. Finally, herd behavior describes following the crowd rather than acting on independent analysis, which amplifies price movements and contributes to market instability, particularly where managers face career risk for deviating from peers (Haddad et al., 2025).

2.2 Current Literature

The traditional efficient markets hypothesis (Fama, 1970) holds that prices fully reflect all available information, with any deviations quickly corrected by rational arbitrageurs. Behavioral finance challenges this view, arguing that systematic biases, overconfidence chief among them, produce persistent distortions in both individual decision-making and aggregate market outcomes. The debate has since shifted toward how overconfidence originates at the individual level and how it transmits into observable market outcomes such as trading volume and mispricing, with comparatively less attention paid to whether it also shapes how households construct their portfolios.

Most directly relevant to this study's framework is Daniel et al. (2015), whose overconfidence-based asset pricing model has investors overweighting private signals relative to public information. It generates predictions of excess trading volume, return momentum, and long-run reversals that are broadly confirmed in securities market data, establishing why individual-level overconfidence should produce detectable market-level consequences. Gödker et al. (2025) complement this by adding micro-level evidence, combining transaction records and survey data from Dutch retail investors with a controlled experiment to show that the disposition effect causally generates overconfidence. Investors judge their own skill by realized gains against realized losses, a metric systematically inflated by both the disposition effect and self-serving memory. This gives a precise mechanism connecting individual psychology to excess trading and lower profits.

While the above papers focus primarily on the behavior of individual retail investors, a complementary strand of the literature examines how overconfidence and behavioral distortions interact with institutional and market-level forces. Haddad et al. (2025) estimate a demand system with strategic responses among institutional investors and find that institutional reactions offset only two-thirds of the price impact of any given behavioral change. This incomplete arbitrage result is important for this paper because it implies that overconfident retail trading is not fully corrected by more sophisticated market participants, allowing the behavioral distortions documented by Daniel and Hirshleifer (2015) and Gödker et al. (2025) to persist in prices. Singh et al. (2024) complement this institutional perspective by conducting a systematic review of 132 studies on financial overconfidence across 84 journals, confirming that overconfidence is associated with excessive risk-taking, poor diversification, and higher trading frequency across a range of investor types, while also noting that consequences for market-level outcomes remain underexplored relative to individual-level determinants.

Zooming back to the household level, Inghelbrecht and Tedde (2024) provide some of the most direct empirical evidence linking overconfidence in financial literacy to trading behavior, bridging the individual-level mechanisms identified by Gödker et al. (2025) and the market-level implications raised by Haddad et al. (2025). Using a unique Belgian brokerage dataset and MiFID test scores as an objective measure of financial knowledge, they find that overconfident investors engage in more frequent trading and incur higher transaction costs, with both effects increasing as overconfidence levels rise. Crucially, they also find that overconfident investors do not necessarily perform worse than rational investors, as higher overconfidence enables some investors to embrace more risk and potentially benefit from the market risk premium. Their use of an objective financial literacy test to measure overconfidence, comparing tested knowledge against self-assessed ability, directly parallels the KNOWL versus FINLIT gap measure constructed in this paper, lending methodological support to the approach adopted here.

Extending the study of overconfidence beyond retail investors to the corporate level, Malmendier and Tate (2005) show that the same psychological bias identified by Daniel and Hirshleifer (2015) produces analogous distortions in managerial decision-making, with overconfident CEOs overestimating the returns to their investment projects and systematically overinvesting when internal funds are available. Their identification strategy, classifying CEOs as overconfident if they persistently hold in-the-money stock options beyond the optimal exercise date, offers a behaviorally grounded proxy for overconfidence that complements the survey-based measures used in household finance research. Taken together, the retail, institutional, and managerial strands of this literature point to the same conclusion: overconfidence, wherever it appears, produces systematic and predictable deviations from rational decision-making with measurable consequences for investment behavior.

2.3 Gap in the Literature

Despite the substantial body of evidence reviewed above, several important gaps remain. First, as Singh et al. (2024) note, the existing literature has focused predominantly on the determinants of overconfidence rather than its behavioral consequences, with comparatively little work directly linking the overconfidence gap to specific investment decisions such as trading frequency and portfolio diversification at the household level. Second, most empirical studies of retail investor overconfidence rely on brokerage data from specific institutions or single countries, such as the Dutch investors in Gödker et al. (2025), raising questions about whether the findings generalize to the broader US household population. Third, the overconfidence gap measure, the difference between self-assessed and objectively measured financial knowledge, has been used extensively in financial literacy research but has rarely been applied to directly explain trading behavior and portfolio concentration in a nationally representative US sample. This paper addresses all three gaps. By doing so it moves beyond the single-institution brokerage datasets that dominate the existing literature, responds directly to the call in Singh et al. (2024) for research connecting individual overconfidence to observable investment decisions, and contributes a replicable measurement approach using the KNOWL versus FINLIT gap from a publicly available federal dataset that future researchers can apply to earlier or later SCF waves.

3. Data Sources

3.1 Dataset Description

The data used in this paper comes from the 2022 Survey of Consumer Finances (SCF), which is a large survey of American households run by the Federal Reserve, which is the central bank of the United States. The survey was carried out between April and December 2022, and questions about income refer to the 2021 calendar year.

The version of the dataset used here contains information on 4,595 households across 22,975 rows. The reason there are more rows than households is that the Federal Reserve fills in uncertain answers five different ways for each household, producing five copies of each household's data called "implicates." This is a standard technique used to make sure missing or unclear responses do not bias the results. For descriptive analysis, only the first implicate is used to simplify presentation, giving a working sample of 4,529 households. The 66 respondents who recorded a value of -1 on the KNOWL variable are recoded to 0 rather than removed, as -1 is the SCF's internal code for a genuine answer of zero and treating it as missing would incorrectly exclude the least confident households from the analysis. The full dataset includes 357 variables covering topics from household income and debt to attitudes toward risk and investment behavior.

The Survey of Consumer Finance deliberately oversamples wealthy households because they own a disproportionate share of US financial assets, meaning raw averages for income and net worth are skewed upward by a small number of extremely wealthy households. For this reason, this paper reports weighted means alongside medians for financial variables, using survey weights (WGT/5) to produce population-representative estimates

3.2 Key Variables

Table 1. Key Variable Definitions

Variable	Definition	Variable	Definition
OCGAP	Overconfidence gap = $z(\text{KNOWL}) - z(\text{FINLIT})$. Positive values indicate overconfidence.	NSTOCKS	Number of distinct stocks held directly (diversification).
KNOWL	Self-rated financial knowledge (1–10).	HEQUITY	Holds any equity, direct or indirect (participation decision).
FINLIT	Objective financial literacy score (0–3 questions correct).	HBROK	Has a brokerage account.
HTRAD	Traded securities through a broker in the past year (trading intensity).	DEQ_SHARE	Share of total equity held as directly selected individual stocks.
NTRAD	Number of trades executed through a broker in the past year.	YESFINRISK	Willing to take above-average financial risk.

The OCGAP variable above, or the overconfidence gap, is constructed as the difference between the z-scored self-rated financial knowledge score (KNOWL, rated on a scale of 1 to 10) and the z-scored objective financial literacy score (FINLIT, scored 0 to 3 based on correct responses to three standard financial literacy questions). Standardizing both measures prior to subtraction places them on a common scale and ensures that OCGAP reflects relative miscalibration rather than level differences between the two instruments. A positive value of OCGAP indicates that a household rates its own financial knowledge above what its objective test performance would justify, the operational definition of overconfidence adopted in this paper. A positive OCGAP indicates miscalibration, that is, self-assessed knowledge exceeds what objective performance would justify, rather than high absolute confidence levels.

3.3 Data Strengths and Limitations

The SCF offers several strengths for this research question. Its national representativeness addresses a limitation common to single-institution brokerage studies, and the simultaneous availability of both KNOWL and FINLIT within the same survey allows a direct, in-sample construction of the overconfidence gap without merging data across sources. The SCF's detailed portfolio composition data also enables a richer characterization of investment behavior than surveys capturing only total wealth.

That said, several limitations apply. The cross-sectional nature of the SCF prevents causal identification: the association between OCGAP and trading could reflect reverse causality, whereby more active traders develop inflated self-assessments through self-serving attribution of past gains (Gödker et al., 2025). The results should therefore be interpreted as associations rather than causal effects. All responses are self-reported, though this concern is mitigated by the SCF's status as a federally administered survey with established data quality controls. The findings are also specific to US households and are not intended to generalize internationally.

3.4 Data Summary

Table 2 presents weighted summary statistics for the full sample of 4,595 households. The two headline variables reveal the overconfidence pattern at the core of this paper: the average self-rated financial knowledge score (KNOWL) is 7.26 out of 10, while the average objective literacy score (FINLIT) is 2.23 out of 3, or roughly 74% correct. Confidence runs notably higher than tested knowledge. The overconfidence gap (OCGAP) averages near zero by construction. On the investment side, 67% of households traded in the past year (HTRAD) and 26% hold a brokerage account (HBROK), confirming that active investing is the exception rather than the norm. Income and net worth are heavily right-skewed, with median income of \$70,259 and median net worth of \$192,700 sitting well below their respective means, which is why weighted medians are the preferred summary for these variables.

Table 2. Weighted summary statistics for key variables, Survey of Consumer Finances 2022 ($n = 4,595$ households).

Sample	Variable	Mean	SD	Median	Min	Max	Households
All households	KNOWL	7.26	2.16	8.00	0.00	10.00	4595
All households	FINLIT	2.23	0.81	2.00	0.00	3.00	4595
All households	OCGAP	0.00	1.30	-0.14	-4.31	4.01	4595
All households	AGE	52.45	17.61	52.00	18.00	95.00	4595
All households	KIDS	0.71	1.10	0.00	0.00	10.00	4595
All households	INCOME	141390.00	727962.00	70259.00	0.00	458230949.40	4595
All households	NETWORTH	1059457.00	8085433.00	192700.00	-555500.00	2387780900.00	4595
All households	FIN	503056.00	4580118.00	36810.00	0.00	2119722000.00	4595
All households	HBROK	0.26	0.44	0.00	0.00	1.00	4595
All households	HSTOCKS	0.21	0.41	0.00	0.00	1.00	4595
All households	HEQUITY	0.58	0.49	1.00	0.00	1.00	4595
All households	ISELF	0.08	0.27	0.00	0.00	1.00	4595
All households	IFINPRO	0.29	0.46	0.00	0.00	1.00	4595
All households	YESFINRISK	0.04	0.19	0.00	0.00	1.00	4595
Brokerage holders	NTRAD	27.23	194.41	2.00	0.00	6250.00	1683
Brokerage holders	HTRAD	0.67	0.47	1.00	0.00	1.00	1683
Stockholders	NSTOCKS	10.40	20.02	4.00	1.00	150.00	1338
Equity holders	DEQ_SHARE	0.27	0.38	0.00	0.00	1.00	2897

3.5 Visualisations

Figure 1 (below) maps the pairwise correlations between all key variables used in the analysis. The strongest relationship in the matrix is between FINLIT and OCGAP at -0.64 , which is expected since the overconfidence gap is constructed directly from the literacy score. Beyond this mechanical relationship, correlations between OCGAP and the investment behavior variables (LOG_NTRAD, NSTOCKS, DEQ_SHARE) are all close to zero, suggesting that the raw bivariate relationship between overconfidence and investment behavior is modest, indicating that regression analysis controlling for other variables is necessary to better evaluate the association.

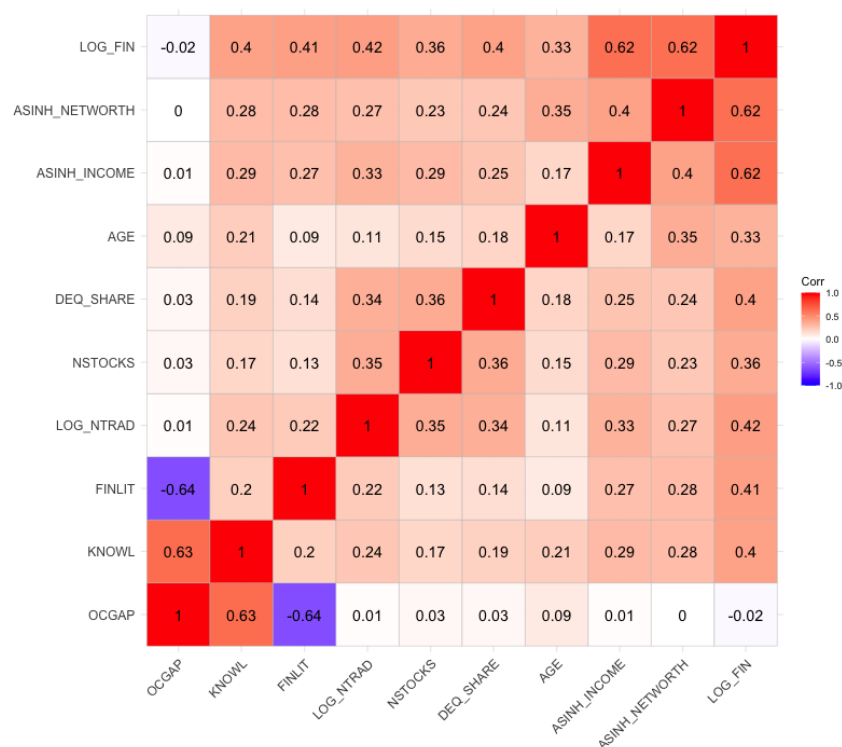


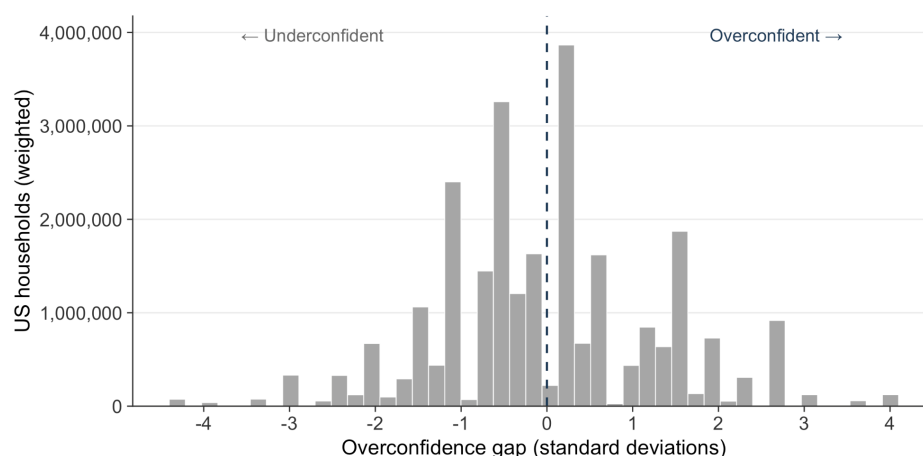
Figure 1. Correlation matrix of key variables.

Figure 2 (below) sorts households by the size of their overconfidence gap and counts how many fall into each range, weighted to represent the full US population rather than just the survey sample. The distribution is concentrated around zero, indicating broadly calibrated self-assessment for much of the sample, but it also displays a pronounced positive tail. This suggests that substantial overestimation is concentrated among a smaller, economically meaningful subset of households.

Figure 3 (below) compares self-rated financial knowledge, on a 0 to 10 scale, against scores on an objective literacy test, out of 3 questions correct. Each box plot shows the median and the middle 50% of responses, with the navy diamond marking the weighted mean for each literacy score group, letting us see the full spread of self-perception at every level of actual knowledge. The result is stark. Households that answered none of the three basic financial literacy questions correctly ($n = 150$) still rated their subjective knowledge at a weighted mean of 6.5 out of 10. This reveals notable miscalibration: despite failing to demonstrate basic competence on core concepts like interest compounding, inflation, and risk diversification, these households still evaluate their financial knowledge well above the scale's midpoint. This pattern suggests that poor financial literacy does not automatically produce low self-ratings; rather, it is the gap between what people know and what they think they know that characterizes overconfidence as measured here. The boxes do rise slightly as literacy scores increase, from a median of 7 at zero correct to a median of 8 at three correct ($n = 2,339$), so self-perception is not completely disconnected from reality. However, self-rated knowledge never falls as low as objective performance would suggest it should. Even households who answered every question incorrectly still rated themselves above the midpoint of the confidence scale, and it is precisely this disconnect between what people know and what they think they know that this paper sets out to explain. Brokerage account holders show a non-monotonic trading pattern across overconfidence groups, peaking at 78% in group 4 before dropping to 65% in the most overconfident group, suggesting regression analysis is needed to isolate overconfidence from confounding factors.

Figure 2. Distribution of the overconfidence gap

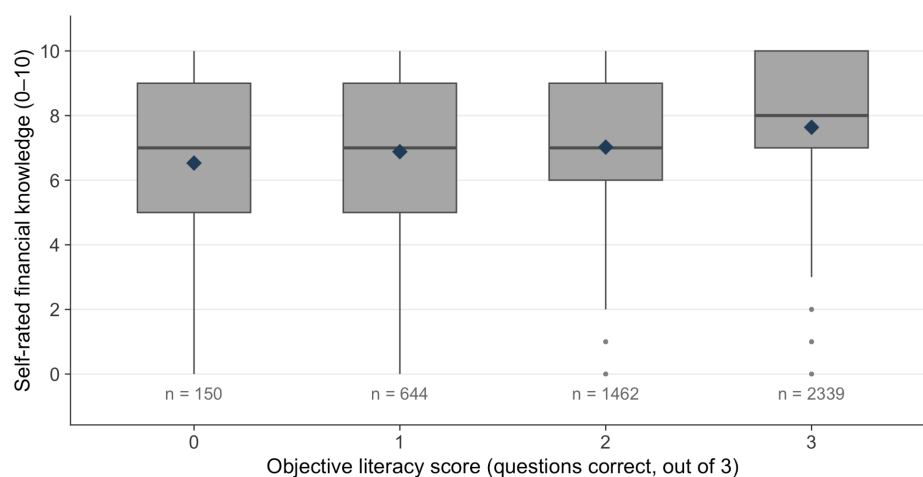
Most households are roughly calibrated, but there is a long overconfident tail



Notes: Overconfidence gap = $z(\text{KNOWL}) - z(\text{FINLIT})$. Positive values indicate a household rates its own financial knowledge above what its objective literacy score justifies. Weighted using WGT/5.
Source: Survey of Consumer Finances 2022, $n = 4,595$ households.

Figure 2. Distribution of the overconfidence gap.**Figure 3. Self-rated knowledge by objective financial literacy**

Households answering none of the three questions correctly still rate themselves above the midpoint



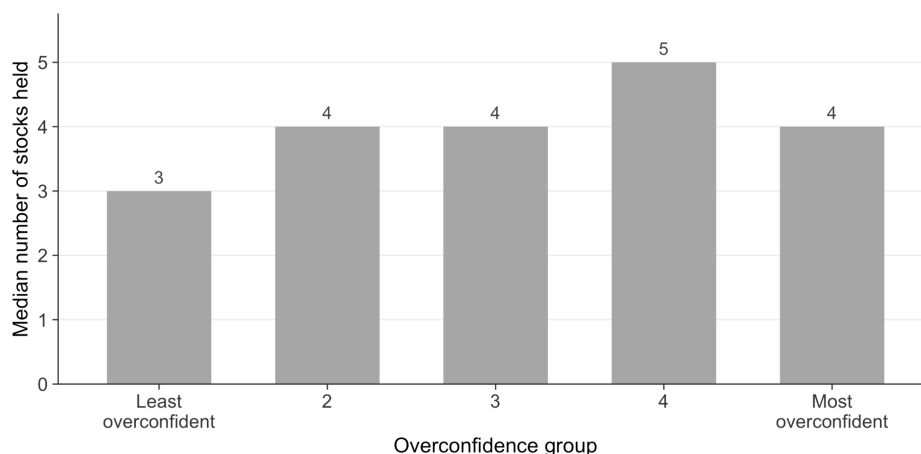
Notes: Boxes show the median and interquartile range. Navy diamonds show the weighted mean.
Sample sizes are households. Source: Survey of Consumer Finances 2022.

Figure 3. Self-rated knowledge by objective financial literacy.

Figure 4 (below) tracks the median number of individual stocks held by stockholders across the same five overconfidence groups, using the median instead of the mean because one household in the sample holds 150 different stocks and would distort any average. The least overconfident group holds a median of 3 stocks, rising to 4 in groups 2 and 3, peaking at 5 in group 4, before falling back to 4 in the most overconfident group. The pattern is not a straight line in either direction. The most overconfident group does not hold the fewest stocks, which would be the expected result if overconfidence consistently produced concentrated portfolios. Instead the relationship follows a slight hump shape, peaking in group 4. This suggests that overconfidence alone does not straightforwardly predict how many distinct stocks a household owns, and that wealth and risk tolerance, both of which increase the capacity and willingness to hold more securities, likely play a larger role in determining portfolio breadth.

Figure 4. Portfolio concentration across the overconfidence distribution

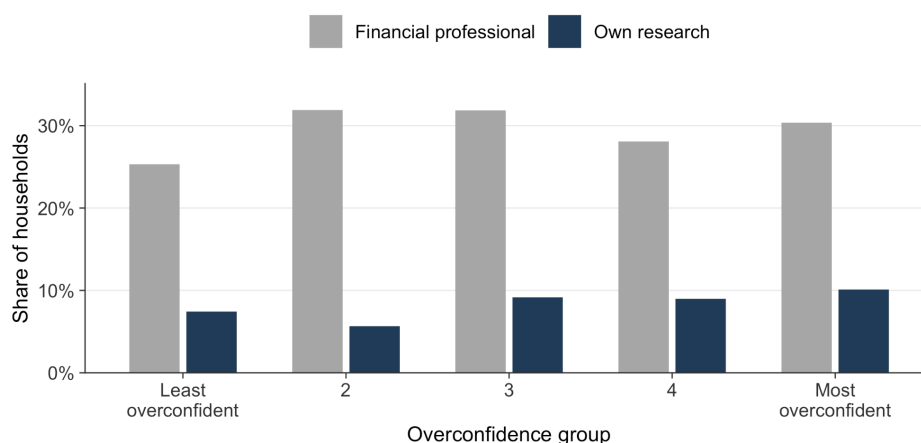
Number of different companies held, among households owning individual stocks



Notes: The median is used rather than the mean because holdings are highly skewed (one household holds 150 different stocks). Sample restricted to households owning individual stocks ($n \approx 1,338$).
Source: Survey of Consumer Finances 2022.

Figure 4. Portfolio concentration across the overconfidence distribution.**Figure 5. Sources of investment information**

Share of households relying on their own research versus a financial professional



Notes: Shares are weighted using WGT/5. All households, $n = 4,595$. A household can report more than one information source, so the bars do not sum to 100 per cent.
Source: Survey of Consumer Finances 2022.

Figure 5. Sources of investment information.

Figure 5 (above) sets two behaviors side by side across the five overconfidence groups: the share of households relying on a financial professional and the share relying on their own research. Financial professionals win every single group by a wide margin. In the least overconfident group, 26% use a financial professional compared to just 8% who rely on their own research. This gap is consistent across all five groups, with financial professional use ranging from roughly 26% to 32% and own research ranging from 6% to 10%. Even the most overconfident group leans on outside expertise more than self-directed research, at 31% versus 10%. If overconfidence meant rejecting outside help in favor of self-reliance, we would expect that gap to close or reverse in the most overconfident group. It does not. Overconfidence, as measured here, does not translate into self-reliance in how households gather investment information.

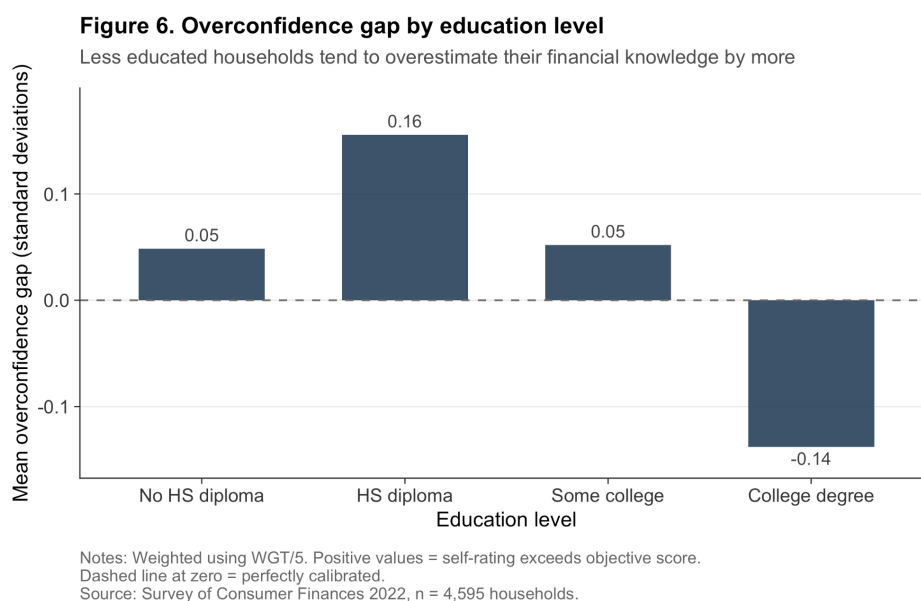


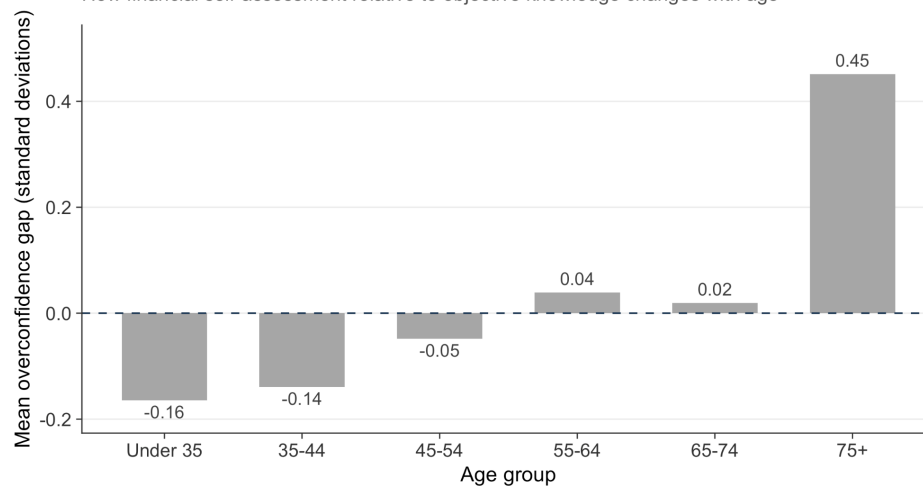
Figure 6. Overconfidence gap by education level.

Figure 6 (above) breaks the average overconfidence gap down by education level. Three of the four groups post a positive gap, meaning they rate their own financial knowledge above what their objective test score justifies: no high school diploma at 0.05, high school diploma at 0.16, and some college at 0.05. High school graduates show the largest positive gap in the figure. College-educated households are the only group running negative at -0.14 , meaning on average they are slightly underconfident rather than overconfident. This pattern is consistent with the Dunning-Kruger effect (Kruger & Dunning, 1999): limited exposure to a subject can mask the limits of one's own understanding, while a college degree appears to sharpen self-awareness and produce more accurate self-assessment.

Figure 7 (below) tracks the average overconfidence gap across six age brackets, from under 35 to 75 and older. Households under 35 run underconfident at -0.16 , and this underconfidence continues through the 35 to 44 bracket at -0.14 and the 45 to 54 bracket at -0.05 . By 55 to 64 the gap turns slightly positive at 0.04, and remains near zero at 0.02 for the 65 to 74 group. Then the pattern breaks entirely. Households aged 75 and older post a gap of 0.45, the largest bar in the entire figure by a wide margin, more than triple the size of any other bar. Confidence and accuracy track closely together for most of adulthood, then diverge sharply at the oldest end of the sample. Age does not guarantee accurate self-assessment. Past a certain point, it may produce the opposite effect, with years of experience feeding a sense of expertise that outpaces actual, current financial knowledge.

Figure 7. Overconfidence gap by age group

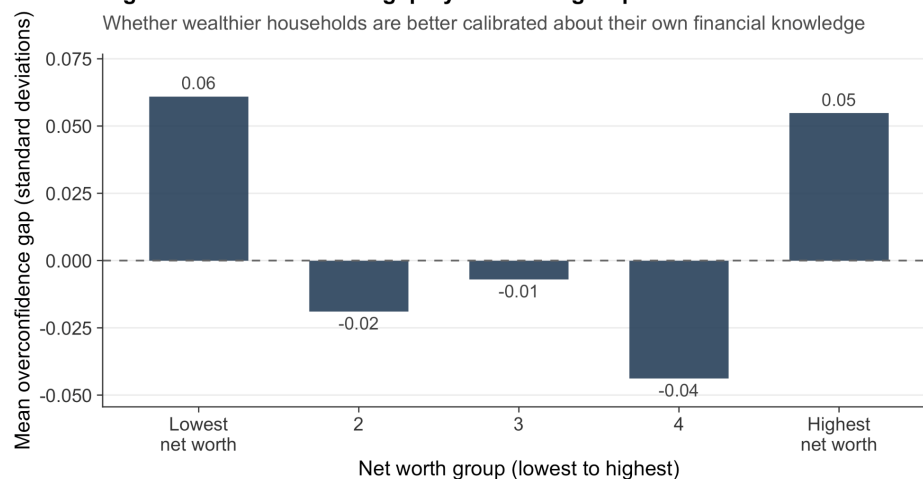
How financial self-assessment relative to objective knowledge changes with age



Notes: Weighted using WGT/5. Dashed line at zero = perfectly calibrated.
 Source: Survey of Consumer Finances 2022, n = 4,595 households.

Figure 7. Overconfidence gap by age group.**Figure 8. Overconfidence gap by net worth group**

Whether wealthier households are better calibrated about their own financial knowledge



Notes: Households split into five equal groups by asinh(net worth). Asinh transformation used because net worth can be zero or negative. Positive gap = self-rating exceeds objective score. Weighted using WGT/5. n = 4,595 households.
 Source: Survey of Consumer Finances 2022.

Figure 8. Overconfidence gap by net worth group.

Figure 8 (above) splits households into five equal-sized groups by net worth, from lowest to highest, and tracks the average overconfidence gap in each. The lowest net worth group posts a gap of 0.06, the largest positive value in the figure. The three middle groups all run slightly negative, at -0.02 , -0.01 , and -0.04 respectively. The highest net worth group then ticks back up to 0.05, nearly matching the lowest group. That is not the pattern we would expect if wealth alone explained financial self-awareness. If greater wealth translated into more experience and therefore better calibration, we would expect a steady decline from left to right. Instead the gap dips in the middle and rises again at both ends. Wealth does not produce a straight-line improvement in self-assessment accuracy. Money buys options. It does not buy calibration.

4. Methodology

4.1 Research Design

The SCF addresses item non-response and measurement uncertainty through multiple imputation, producing five complete datasets, referred to as implicates, for each sampled household. Analysing the five implicates as independent observations inflates the effective sample size fivefold and produces standard errors that are artificially narrow, leading to over-rejection of the null hypothesis. To correct for this, all regression models are estimated separately on each of the five implicates and the results are combined using Rubin's (1987) combining rules, which pool the within-imputation and between-imputation variance components to produce valid standard errors that account for imputation uncertainty.

4.2 Hypotheses

- H1: Households with a larger overconfidence gap trade more actively, as measured by the log number of securities trades executed through a broker in the past year.
- H2: Households with a larger overconfidence gap hold less diversified portfolios, as measured by the number of distinct stocks held directly.

4.3 Regression Framework

To test H1, the following sequence of OLS models is estimated on the subsample of households with an active brokerage account. The trading outcome is restricted to this subsample because households without a brokerage account report zero trades by structural necessity rather than by choice, and including them would conflate the decision to open a brokerage account with the decision to trade actively within one.

The dependent variable, LOG_NTRAD, is the natural logarithm of one plus the number of securities trades executed through a broker in the past year. The log transformation is applied because raw trade counts are heavily right-skewed, with one household in the sample reporting 6,250 trades, and the logarithmic scale ensures that extreme observations do not disproportionately influence the estimates.

The four regression models are:

- **Model 1 (Baseline):**

$$\text{LOG_NTRAD} = \beta_0 + \beta_1 \text{OCGAP} + \varepsilon$$

- **Model 2 (+ Demographics):**

$$\text{LOG_NTRAD} = \beta_0 + \beta_1 \text{OCGAP} + \beta_2 \text{AGE} + \beta_3 \text{HHSEX} + \beta_4 \text{EDCL} + \varepsilon$$

- **Model 3 (+ Wealth and Income):**

$$\begin{aligned} \text{LOG_NTRAD} = & \beta_0 + \beta_1 \text{OCGAP} + \beta_2 \text{AGE} + \beta_3 \text{HHSEX} + \beta_4 \text{EDCL} \\ & + \beta_5 \text{ASINH_INCOME} + \beta_6 \text{LOG_FIN} + \varepsilon \end{aligned}$$

- **Model 4 (Full model):**

$$\begin{aligned} \text{LOG_NTRAD} = & \beta_0 + \beta_1 \text{OCGAP} + \beta_2 \text{AGE} + \beta_3 \text{HHSEX} + \beta_4 \text{EDCL} \\ & + \beta_5 \text{ASINH_INCOME} + \beta_6 \text{LOG_FIN} + \beta_7 \text{YESFINRISK} + \varepsilon \end{aligned}$$

To test H2, the identical four-model sequence is estimated on the subsample of households holding individual stocks directly, replacing LOG_NTRAD with NSTOCKS, the count of distinct stocks held. Households with no direct stockholdings report NSTOCKS equal to zero by construction rather than as a behavioral choice, so restricting the sample to direct stockholders isolates variation in diversification conditional on market participation.

Demographic controls are added sequentially across the four models to assess the robustness of the OCGAP coefficient to potential confounding. Age, sex, and education are included in Model 2 because each is associated with both financial literacy and investment behavior in the existing literature, raising

the possibility that a raw correlation between OCGAP and trading reflects differences in these background characteristics rather than overconfidence per se. Income and financial wealth, both transformed using the inverse hyperbolic sine and log transformations respectively to accommodate zero and negative values (Burbidge et al. 1988), are added in Model 3 because wealthier households have both greater capacity and greater incentive to trade actively. Self-reported willingness to take above-average financial risk (YESFINRISK) is added in Model 4 to separate the effect of overconfidence from general risk tolerance, since the two constructs may be correlated but represent conceptually distinct channels through which psychological factors influence investment behavior.

The stepwise addition of controls serves a diagnostic purpose: if the coefficient on OCGAP diminishes substantially as controls are introduced, the baseline association is likely attributable in part to demographic or wealth heterogeneity. If OCGAP remains statistically and economically significant in Model 4, this constitutes evidence that the overconfidence gap has an independent association with investment behavior beyond what is explained by observable household characteristics.

5. Results and Discussion

5.1 Main Results

Throughout the regression tables, significance stars indicate the probability that an estimated coefficient could have occurred by chance if the true effect were zero; three stars ($p < 0.01$) means this probability is less than 1%, providing strong evidence of a real effect (Field, 2013).

Table 3. Does Overconfidence Predict Trading Activity?

Dependent variable: LOG_NTRAD (log number of trades). Sample: brokerage-account holders ($n = 1,683$).

	Model 1	Model 2	Model 3	Model 4
OCGAP	0.063* (0.035)	0.120*** (0.036)	0.122*** (0.036)	0.116*** (0.035)
AGE		-0.004* (0.002)	-0.009*** (0.002)	-0.008*** (0.002)
HHSEX (Female)		-0.578*** (0.096)	-0.419*** (0.099)	-0.421*** (0.099)
EDCL (HS diploma)		-0.355 (0.331)	-0.497 (0.330)	-0.501 (0.329)
EDCL (Some college)		0.060 (0.322)	-0.088 (0.322)	-0.066 (0.320)
EDCL (College degree)		0.262 (0.313)	-0.034 (0.316)	-0.019 (0.314)
ASINH_INCOME			0.103*** (0.028)	0.109*** (0.028)
LOG_FIN			0.063*** (0.024)	0.058** (0.024)
YESFINRISK				0.578*** (0.180)
Constant	1.473*** (0.037)	1.657*** (0.350)	0.048 (0.459)	-0.059 (0.453)
Implicates combined (Rubin)	Yes	Yes	Yes	Yes
Households	1,683	1,683	1,683	1,683

Notes: Standard errors in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. OLS with survey weights (WGT/5). Standard errors corrected for multiple imputation using Rubin's (1987) combining rules.

Table 3 presents the Rubin-combined OLS estimates for H1. The coefficient on OCGAP can be interpreted as the effect of being miscalibrated about one's financial knowledge, holding the absolute level of confidence constant. The coefficient is positive and statistically significant across all four models, providing consistent support for H1. In Model 4, a one-point increase in the overconfidence gap is

associated with a 12.3% increase in trading activity, calculated as $100 \times (\exp(0.116) - 1)$ following the standard log-level interpretation (Wooldridge, 2019). The raw bivariate relationship in Model 1 is modest ($\beta = 0.063$, $p < 0.1$). Notably, the coefficient strengthens when demographic controls are added in Model 2 ($\beta = 0.120$, $p < 0.01$), and remains stable across Models 3 and 4 at 0.122 and 0.116 respectively, both statistically significant at the 1% level.

Among the control variables, two patterns are worth noting. Female-headed households trade significantly less than male-headed households across all specifications in which the control appears, with the coefficient on HHSEXFemale ranging from -0.419 to -0.421 , consistent with the well-established finding in the household finance literature that male investors trade more actively than female investors. Age is negatively associated with trading throughout all models, and more strongly so once wealth is controlled for. Willingness to take above-average financial risk (YESFINRISK) is positively and significantly associated with trading activity in Model 4 ($\beta = 0.578$, $p < 0.01$), confirming that risk tolerance and overconfidence are distinct but complementary drivers of active trading. Crucially, the OCGAP coefficient remains significant at the 1% level in Model 4 even after controlling for risk tolerance, indicating that overconfidence has an independent association on trading activity beyond general risk preferences. Education, income, and financial wealth are all positively associated with trading frequency - aligning with expected directional associations. However, education is not significantly associated with trading in any specification.

Table 4. Does Overconfidence Predict Under-Diversification?

Dependent variable: NSTOCKS (number of distinct stocks held). Sample: direct stockholders ($n = 1,338$).

	Model 1	Model 2	Model 3	Model 4
OCGAP	1.547*** (0.528)	1.326** (0.532)	1.581*** (0.513)	1.516*** (0.512)
AGE		0.120*** (0.034)	-0.051 (0.037)	-0.040 (0.037)
HHSEX (Female)		-2.791* (1.599)	0.688 (1.600)	0.477 (1.607)
EDCL (HS diploma)		5.522 (4.409)	4.450 (4.247)	4.116 (4.232)
EDCL (Some college)		4.950 (4.285)	2.553 (4.139)	2.668 (4.124)
EDCL (College degree)		9.630** (4.185)	3.404 (4.092)	3.329 (4.076)
ASINH_INCOME			0.638 (0.443)	0.702 (0.441)
LOG_FIN			2.716*** (0.334)	2.648*** (0.335)
YESFINRISK				8.236*** (2.697)
Constant	10.586*** (0.550)	-3.147 (4.613)	-31.644*** (6.260)	-32.437*** (6.226)
Implicates combined (Rubin)	Yes	Yes	Yes	Yes
Households	1,338	1,338	1,338	1,338

Notes: Standard errors in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. OLS with survey weights (WGT/5). Standard errors corrected for multiple imputation using Rubin's (1987) combining rules.

Contrary to H2, the coefficient on OCGAP is positive and statistically significant across all four specifications: more overconfident households hold more distinct stocks rather than fewer. In the full model (Model 4), a one-point increase in the overconfidence gap is associated with holding 1.52 more distinct stocks ($\beta = 1.516$, Wooldridge, 2019). Scaling by OCGAP's standard deviation of 1.30 (Table 2), a one standard deviation increase in overconfidence is associated with holding approximately $1.516 \times 1.30 = 1.97$ additional unique stocks. This result is consistent across all four models. The result is robust to the inclusion of demographic controls, wealth and income, and risk tolerance.

This finding runs counter to the under-diversification hypothesis and warrants careful interpretation. One plausible explanation is that overconfident households, trusting their stock-picking ability, are more willing to enter the market; as a result, holding multiple individual positions naturally leads to a higher stock count. Under this interpretation, overconfident households are not better diversified in a meaningful risk-reduction sense; they simply hold more individual bets, each representing a concentrated conviction rather than a deliberate diversification strategy. A second possibility is that NSTOCKS, as a raw count of distinct holdings, is an imperfect proxy for true diversification. A household holding 20 stocks concentrated in a single sector, such as technology or energy, remains highly exposed to sector-specific shocks and would score poorly on any correlation-based measure of risk reduction, yet would score highly on NSTOCKS. Genuine diversification requires not just a larger number of holdings but holdings whose returns move independently of one another, a dimension that NSTOCKS cannot capture. These interpretive limitations are discussed further in Section 5.3.

Among the control variables in H2, financial wealth (LOG_FIN) is strongly and positively associated with the number of stocks held ($\beta = 2.716$ to 2.648 , $p < 0.01$ across Models 3 and 4), reflecting the straightforward fact that wealthier households have more capital to deploy across individual securities. Willingness to take above-average financial risk (YESFINRISK) is positively associated with the number of stocks held in Model 4 ($\beta = 8.236$), and its magnitude is by far the largest of any variable in the model, dwarfing the OCGAP coefficient and comparable only to the college degree education coefficient, suggesting that risk tolerance is a substantially stronger predictor of how many stocks a household holds than overconfidence itself. In Model 2, college-educated households hold significantly more distinct stocks than households with no high school diploma, the baseline category ($\beta = 9.630$), though this coefficient falls substantially once financial wealth is included in Models 3 and 4 and loses statistical significance.

5.2 Policy Implications

The finding that overconfidence is associated with higher trading activity carries direct implications for financial regulation and investor protection. High trading frequency is consistently linked to lower net returns (Barber et al. 2000), through transaction costs and active traders engaging in poor market timing. If overconfident households overtrade relative to what their actual financial knowledge justifies, they are likely incurring avoidable costs that compound into meaningful wealth losses. This suggests that policy interventions aimed at improving the calibration of financial self-assessment, rather than simply raising the level of financial knowledge, may be of particular value.

Financial literacy education programs have historically focused on raising objective knowledge scores. The results of this paper suggest a second dimension is needed: helping individuals assess the limits of what they know. A household aware that it does not fully understand the stock market is less likely to overtrade on the basis of false confidence than one that scores highly on self-assessment but poorly on objective tests. Regulators designing mandatory financial education requirements, such as those attached to retirement account enrollment or mortgage origination, could incorporate self-calibration exercises alongside standard literacy content.

These results also have implications for retail investment platform design. The rapid expansion of commission-free trading apps has dramatically lowered the transaction cost of overconfident trading, potentially amplifying the welfare costs identified here. Regulators considering whether and how to impose friction on retail trading decisions, such as cooling-off periods or mandatory risk disclosures tied to trading frequency, may find the evidence in this paper relevant to their deliberations.

5.3 Link to Literature

The finding that overconfidence predicts higher trading activity matches Daniel et al.'s (2015) central prediction that overconfident investors overweight private signals relative to public information. Gödker et al. (2025) are also relevant: their disposition-effect mechanism predicts exactly the self-reinforcing cycle the positive OCGAP coefficient in Table 3 reflects.

The H2 result, that overconfident households hold more rather than fewer distinct stocks, neither clearly supports nor contradicts prior work, since brokerage studies document excess trading without examining portfolio breadth (Odean (1998)). The positive relationship between OCGAP and NSTOCKS is more consistent with overconfident households being willing to engage with individual securities at all, holding more separate bets because they trust their judgment on each. Singh, et al. (2024) identify precisely this gap, the consequences of overconfidence for observable investment decisions as underexplored, a gap this paper also addresses.

5.4 Limitations of H2

H2 is not supported by the data. More overconfident households hold more distinct stocks, not fewer. This likely reflects a greater willingness to participate in individual equity markets rather than meaningful risk reduction, since a raw count of holdings cannot measure whether those positions are genuinely uncorrelated across sectors or asset classes. What cannot be determined from this data is whether overconfident investors are genuinely better diversified by risk, which would require correlation analysis of actual portfolio holdings, or simply accumulating more individual bets. Future research linking portfolio compositions to realized volatility or sector concentration ratios would clarify this distinction.

6. Conclusion

6.1 Summary of the Paper

This paper set out to answer the question of whether US households that overestimate their own financial knowledge trade more actively and hold less diversified portfolios. Using microdata from the 2022 Survey of Consumer Finances, a nationally representative sample of 4,595 US households, this paper constructed a household-level overconfidence gap by subtracting the z-scored objective financial literacy score (FINLIT) from the z-scored self-rated financial knowledge score (KNOWL). This gap measures the degree to which a household believes it knows more than its actual test performance justifies. OLS regression models were then estimated separately on the five imputed copies of each household and combined using Rubin's (1987) rules to produce valid standard errors, with trading activity (LOG_NTRAD) tested on the brokerage-account subsample and portfolio concentration (NSTOCKS) tested on the direct stockholder subsample.

The results provide consistent support for H1 and a more nuanced picture for H2. A one-point increase in the overconfidence gap is associated with a 12.3% increase in trading activity, and this relationship is robust to the inclusion of demographic, wealth, income, and risk-tolerance controls. For H2, contrary to the under-diversification hypothesis, more overconfident households hold more distinct stocks rather than fewer, a finding that is interpreted as reflecting greater willingness to engage with individual securities markets rather than genuine risk-reducing diversification.

6.2 Main Takeaway

The central finding of this paper is that overconfidence, measured as the gap between how knowledgeable a household believes itself to be and how knowledgeable it actually is, is a statistically and economically significant predictor of trading activity among US households with brokerage accounts. This result holds after controlling for age, sex, education, income, financial wealth, and risk tolerance, suggesting that overconfidence has an independent effect on investment behavior beyond what is explained by observable household characteristics. The finding is consistent with the theoretical predictions of Daniel and Hirshleifer (2015) and the micro-level experimental evidence of G dker, et al. (2025), and extends both by demonstrating the relationship in a large, nationally representative US household survey rather than a single brokerage dataset or controlled experiment.

6.3 Wider Implications

The findings carry direct implications for financial regulators, policymakers, and the designers of retail investment platforms. If overconfident households systematically overtrade relative to what their actual

financial knowledge justifies, they are likely incurring avoidable transaction costs and timing losses that compound into meaningful wealth shortfalls over time. This suggests that financial literacy interventions should be designed not only to raise the level of objective knowledge but also to improve the calibration of self-assessment, helping households develop a more accurate understanding of the limits of what they know. Regulators considering mandatory financial education requirements attached to retirement account enrollment, mortgage origination, or retail brokerage access could incorporate self-calibration exercises alongside standard literacy content. Additionally, the rapid expansion of commission-free trading platforms has lowered the cost of overconfident trading and may be amplifying the welfare losses identified here, a consideration relevant to ongoing regulatory discussions about friction in retail investment markets.

6.4 Future Research

Several avenues for future research follow naturally from the limitations of this paper. First, because the SCF is cross-sectional, it is not possible to establish whether overconfidence causes more active trading or whether trading experience shapes confidence levels over time. A panel dataset tracking the same households across multiple SCF waves, or linking SCF respondents to their brokerage records, would allow researchers to test the direction of causality more rigorously. Second, this paper uses a single SCF wave from 2022, a year of significant market volatility following the post-pandemic rally and rapid interest rate increases. Replicating the analysis across multiple SCF waves would reveal whether the overconfidence-trading relationship is stable over time or amplified during periods of market stress, which is itself an important question for understanding the systemic consequences of household-level behavioral biases.

Conflicts of Interest

The author declares that there are no conflicts of interests related to this work.

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