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Asset Pricing with Gambling, Affect Investing, and Overconfidence

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Abstract

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We present a multi-asset model in which behavioral investors each exhibit multiple biases: gambling (deriving direct utility from stock holdings), an affect heuristic (allowing emotions towards firms' products to influence investment decisions), and overconfidence. We support these modeling features via a survey of individual investors. We analyze the joint effects of these features on trading activity, price reactions to information, and expected returns. Gambling amplifies trading volume and overconfident underreaction to public signals. Risk-adjusted expected returns decrease in the strength of the affect heuristic, and this effect is more pronounced when gambling propensity is high. Empirical evidence supports these implications.

“The game of investing is intolerably boring and over-exacting to any one who is entirely exempt from the gambling instinct; whilst he who has it must pay to this propensity the appropriate toll.”

–Keynes (1936)

“We may need to introduce direct utility of trading to explain the existence of speculative markets.”

–Black (1986)

“Another common assumption in asset pricing models is that investors are concerned only with the payoffs from their portfolios; that is, investment assets are not also consumption goods. Apparent violations are plentiful. ”

–Fama and French (2007)

“Perhaps the most robust finding in the psychology of judgment is that people are overconfident”

–De Bondt and Thaler (1995)

1 Introduction

There is reliable evidence that financial market investors may not be characterized by neoclassical notions of risk and reward. For instance, investors appear to treat financial markets as gambling venues ([Gao and Lin 2015](#)), and investment in a firm’s stock (such as Tesla or Apple) appears to be influenced by individuals’ personal preferences (affect) for the firm’s activities and products ([Billett, Jiang, and Rego 2014](#)).¹ What are the implications of such phenomena, where stocks provide direct consumption benefits, for financial markets? How do these phenomena interact with biases in belief formation? We address these issues by first validating the gambling and affect biases, as well as the pervasive beliefs-driven bias of overconfidence ([Lichtenstein, Fischhoff, and Phillips 1982](#)), via survey evidence, and then studying a model that combines these features. Our setting, by

¹For more information on gambling incentives and how brand perceptions influence investment, see [Coventry and Brown \(1993\)](#) and [Frieder and Subrahmanyam \(2005\)](#).

integrating the three elements, allows for an initial treatment of the question: what does equilibrium look like when behavioral elements are jointly considered in the same setting, as opposed to being modeled in isolation? We also derive and empirically test the implications of our model for the cross-section of equities.

In our setting, each stock's future payoff is influenced by both a common factor and a firm-specific component. Further, public signals are available about both systematic and firm-specific components of cash flows. Our model consists of rational and behavioral investors. While rational investors interpret the informativeness of the public signals correctly and maximize the expected utility characterized by neoclassical notions of risk and reward, other investors exhibit three types of behavioral biases.

First, due to a form of overconfidence (Odean 1998; Luo, Subrahmanyam, and Titman 2021), they underestimate the precision of the public signals, as they do not produce the signals themselves. Although overconfidence also involves overestimating the precision of private information signals, these signals are hard to measure. Hence, we do not test the implications of overestimating private signal precision, and consider this case in the Internet Appendix. The underestimation of precision about information they do not themselves produce leads to new implications about stock price drift following public announcements, that we are able to test.

Second, investors perceive a stock to produce a non-monetary payoff beyond its actual level; the incremental payoff varies across stocks. This notion captures the idea that the stock can evoke positive or negative affect, which may arise from brand perceptions, loyalty (Schoenbachler, Gordon, and Aurand 2004; Frieder and Subrahmanyam 2005), or societal norms (e.g., against "sin" companies as discussed in Geczy, Stambaugh, and Levin 2005 and Hong and Kacperczyk 2009). As anecdotal motivation, an article in the *Wall Street Journal* recently characterizes a retail trader as the following: "She said she likes to buy stock in companies whose products she uses, such as Netflix and McDonald's."²

Finally, the behavioral investors derive direct utility from the absolute scale of their stock positions (a gambling propensity), beyond wealth maximization. In equilibrium risk aversion limits the size of this position. This type of gambling propensity reflects the idea that a position (either positive or negative) in a stock increases the "thrill" of gam-

²<https://tinyurl.com/32anvvbv>, 11/29/2025.

bling in financial markets. Anecdotally, our modeling choice is supported by a recent popular press article which quoted a retail investor as “The thrill gets me going...If \$500 can get me \$50,000 or \$60,000, let me just try.”³ Our perspective is also supported by neuropsychological research which shows that the ex ante uncertainty of the reward from gambling triggers the secretion of dopamine, a pleasure-inducing hormone (Preuschoff, Bossaerts, and Quartz 2006; Anselme and Robinson 2007). In our analysis, we allow the gambling propensity parameter to vary in the cross-section.

We justify the preceding assumptions via a survey of almost 500 U.S. retail investors. We find strong support for our premises. Specifically, the majority of our subjects display signs of overconfidence. They also confound investing with familiarity with a company’s products and exhibit proclivity for companies that share their values. Finally, a majority also enjoy trading for its own sake, indicating a gambling motive. These biases exhibit significant cross-correlation across investors.

In our model with the above features (overconfidence, affect, and gambling), trading is triggered because of “agreement to disagree” on the model’s parameters (as also demonstrated by Odean 1998). Particularly, since overconfident investors underestimate the precision of a good (bad) signal and perceive that the resulting high (low) stock price cannot be justified, they become net sellers (buyers). A high level of gambling propensity enables investors to sell (buy) even more aggressively, this amplifies trading volume in equilibrium. Our explanation for high trading volume is consistent with Liu et al. (2022), who find evidence that overconfidence and gambling are primary drivers of trading.⁴

While overconfidence results in underreaction to fundamentals-related variables, gambling scales up this underreaction. The reason is as follows. Behavioral investors underestimate the precision of a good (bad) signal and willingly take the opposite side of rational investors’ trades; this causes price underreaction. A high level of gambling propensity enables them to take an even bigger opposite position; this causes greater underreaction.

³“Traders Are Flooding Markets With Risky Bets. Robinhood’s CEO Is Their Cult Hero, ” *Wall Street Journal* [WSJ], 11/25/2025, <https://tinyurl.com/4n998yc8>. Other articles point out that trading is viewed as entertainment by many investors: “Doctors and counselors say they are seeing more cases of compulsive gambling in financial markets, or an uncontrollable urge to bet. ” (WSJ, 12/20/2024, <https://tinyurl.com/mv24vvuh>) and “Trading and betting has morphed into entertainment for many Americans” (WSJ, 08/11/2025), <https://tinyurl.com/46j4rxbr>).

⁴Dorn and Sengmueller (2009), Markiewicz and Weber (2013), and Gao and Lin (2015) also demonstrate the influence of gambling on trading activity.

We also show that in the cross-section, risk-adjusted returns are lower when the affect heuristic is higher; furthermore, this negative relationship becomes more pronounced when the gambling propensity is high. To understand the intuition behind this, consider stocks for which behavioral investors have a high positive affect. There is high demand for such stocks, leading to overpricing and thus lower future returns relative to other stocks. For stocks with a higher gambling propensity, behavioral investors have an even higher demand; this increases the pressures on stock prices and risk-adjusted returns to a greater extent.

Based on our theoretical analyses, we formulate four main empirical implications:

- (i) In the cross-section of stocks, turnover increases in gambling propensity.
- (ii) Underreaction to public signals is pronounced when gambling propensity is higher.
- (iii) The risk-adjusted return decreases in the affect heuristic; further, this negative relationship becomes more pronounced when gambling propensity is high.

We provide supporting evidence for these implications, using empirical proxies for gambling propensity and affect suggested by previous literature.

Our gambling proxy is motivated by the work of [Kumar \(2009\)](#), who identify a stock as having a high level of gambling propensity if the stock has a low price (i.e., “cheap bet”), high idiosyncratic volatility (i.e., the high variance of the prize distribution), and high idiosyncratic skewness (i.e., small probability of a huge reward). We find that in the cross-section of stocks, turnover increases in the gambling propensity. This finding remains robust after we control for other variables including past stock performance, firm size and age, book-to-market ratio, leverage, earnings volatility, the number of analysts following the firm, analyst forecast dispersion, and (il)liquidity. This evidence supports Implication (i).

To consider Implication (ii) we use the standard finding of [Ball and Brown \(1968\)](#) and [Bernard and Thomas \(1989\)](#) that a company’s stock price continues to drift in the direction of an earnings surprise—a phenomenon known as post-earnings-announcement drift (PEAD). We find that this drift, reflecting price underreaction to earnings news, increases in the gambling propensity. We supplement our analysis by also using [Novy-Marx \(2013\)](#), who finds that firms with high gross margins generate significantly higher returns than

unprofitable firms. We find that the underreaction to profit margins increases in gambling propensity. Our findings remain robust after we control for other variables including past stock performance, firm size, book-to-market ratio, and (il)liquidity. This evidence supports our second implication.

With regard to the affect proxy, [Grullon, Kanatas, and Weston \(2004\)](#) and [Lou \(2014\)](#) propose that a firm's product market advertising promotes brand visibility and affect, and attracts investor attention. Therefore, in our cross-sectional test of stock returns, we measure the affect heuristic for a stock via the corresponding firm's growth of advertising spending. We find that risk-adjusted returns (relative to CAPM and standard factor models) decrease in the growth of advertising spending; further, this negative relationship becomes more pronounced when the gambling propensity is high. These findings remain robust after we control for various variables including past stock performance, firm size, book-to-market ratio, and (il)liquidity. These findings support Implication (iii).

There are other models of investors' gambling incentives based on misperceptions of probabilities to generate a preference for lottery-type stocks, characterized by positively skewed returns. For example, [Barberis and Huang \(2008\)](#) show that if investors overweight small probabilities, a preference for lottery stocks ensues. [Bordalo, Gennaioli, and Shleifer \(2012\)](#) demonstrate that investors may exaggerate the probability of salient (e.g., extreme) payoffs, leading to a preference for lottery stocks.

That individuals may derive direct utility from gambling is well-documented in psychology (see, e.g., [Kuley and Jacobs 1988](#)). The quote from [Black \(1986\)](#) at the beginning of the paper argues for the inclusion of "direct utility of trading" (p. 531) in financial market models to account for the large magnitudes of trading volume observed in real-world speculative markets. Our analysis shows that, consistent with Black's conjecture, gambling preference amplifies trading activity driven by heterogeneous beliefs, such as overconfidence, as demonstrated by [Odean \(1998\)](#). As such, our analysis accords with high volume in financial markets ([Hong and Stein 2007](#)).

Components of our theory have been discussed in previous studies, although not in the same place. For instance, [Daniel, Hirshleifer, and Subrahmanyam \(1998\)](#) study the link between overconfidence and return patterns. [Nagy and Obenberger \(1994\)](#) find that an important reason for stock investment is an individual's feelings for a firm's prod-

ucts and services. [Keloharju, Knüpfer, and Linnainmaa \(2012\)](#) empirically connect stock-holdings with product usage and argue that a “setup in which customer-investors regard stocks as consumption goods, not just as investments, seems to best explain [their] results.” [Friedman and Heinle \(2016\)](#) explore investors’ preferences for particular types of stocks, using the affect heuristic (see also [Luo and Subrahmanyam 2019a](#)). [Luo and Subrahmanyam \(2019b\)](#) introduce the idea that investors derive direct utility from the magnitude of their unsigned positions.

It is worth considering how our paper relates to neoclassical asset pricing. That approach relies on the existence of a pricing kernel that maps future expected cash flows to current market prices (see, e.g., [Cochrane 2009](#)). Within a standard asymmetric information setting (e.g., [Grossman and Stiglitz 1980](#)) the price simply adjusts the expected payoffs (weighted across agents’ beliefs) for a risk premium. In our alternative approach, the utility of trading (gambling) or holding an asset emanates from the direct consumption benefit the asset provides. This direct utility is reflected in the first order conditions, and the market price, via terms not inherent in the neoclassical approach, and this feature leads to our new implications (that we test). We view our approach as complementary to the neoclassical paradigm. We also have a rational arbitraging sector, though they cannot fully arbitrage the mispricing away because they are risk averse and because the asset’s cash flows are risky conditional on their signal.

Another relevant paper is [Koiijen and Yogo \(2019\)](#) (KY). In that paper, investor demands depend on observable characteristics like book and market values of equity, and real investment, and the paper explores implications for this dependence on the cross-section of expected stock returns. In our paper, the parameters governing the affect heuristic and gambling motive are common knowledge but do not directly depend on market prices or firms’ income or investment. Instead, we consider proxies for these parameters, specifically, advertisement spending, and whether the firm’s returns appeal to gambling propensities, in our empirical tests. Thus, we view our paper as complementary to the important work of KY.

There also are alternative theoretical approaches that depart from neoclassical models with rational investors. For instance, [Grinblatt and Han \(2005\)](#) and [Da, Gurun, and Warachka \(2014\)](#) present rationales for underreaction and momentum via the disposition

effect, and the idea that investors pay less attention to news that arrives gradually, as opposed to coming in discrete chunks. [Bordalo et al. \(2020\)](#) show that momentum obtains under extrapolative expectations. [Puri \(2018\)](#) states that the complexity of an asset’s pay-off function dictates its desirability to an investor. While most previous papers, including the preceding ones, examine one behavioral aspect at a time, to our knowledge, we are the first to *combine* behavioral elements to provide new insights on trading activity and asset pricing. Furthermore, we demonstrate that key implications of our theory are supported by empirical evidence.

The rest of this paper is organized as follows. In Section [2](#), we provide the results of a survey that supports our modeling choices. Section [3](#), we describe the setting of our model, and derive and analyze the equilibrium. In Section [4](#), we test the predictions of our model using empirical analysis. Section [5](#) considers some further discussions and extensions, and Section [6](#) concludes.

2 A Survey

We first provide evidence from a survey we conduct to collect evidence on retail investors’ trading behavior. This helps motivate our theoretical analysis. Specifically, we provide evidence that the affect heuristic, a gambling motive, and overconfidence, as indicated in the quotes at the beginning of our paper, are grounded in the reality of why individual investors actually trade.

2.1 The survey sample

We recruit U.S. retail investors through Prolific (<https://www.prolific.com>), a platform that allows researchers to recruit prescreened participants for online surveys and experiments. Out of 688 initial participants, we exclude 196 who either have no brokerage account or have no stock market investments. We exclude another 11 who start but fail to complete the survey. This gives a final sample of 481 participants for our study. The survey questions are provided in Section [IA.1](#) of the Internet Appendix.

Table [1](#) presents summary statistics for the 481 survey participants. Panel A shows that most respondents are male (64.78%), aged 30-50 (32.29% aged 30-40 and 22.43% aged 40-50), hold a Bachelor’s or Master’s degree (51.77% and 22.25%, respectively), and have

invested in the stock market for 4-6 years or more than 10 years (21.21% and 44.07%, respectively).

Panel B of Table 1 shows that at the household level, annual income is concentrated between \$60,000 and \$149,999 (17.05% in the \$60,000-79,000 range, 16.42% in \$80,000-99,000, and 24.12% in \$100,000-149,999). Net worth is concentrated between \$100,000 and \$999,999 (19.54% in \$100,000-249,999, 15.18% in \$250,000-499,999, and 16.84% in \$500,000-999,999). Stock investment is concentrated between \$10,000 and \$249,999 (22.25% in \$10,000-49,999, 16.63% in \$50,000-99,999, and 15.18% in \$100,000-249,999).⁵

Panel C of Table 1 reports the correct response rate for two financial literacy questions. The first question is: “When an investor buys and holds shares of a company, what do they own?” The correct answer is “A partial ownership stake in the company.” The second question is: “When you hold a company’s stock, what kind of payoff might you receive?” The correct answer is “Potential dividends and capital gains if price rises.” The correct rates for these two questions are 91.48% and 95.84%, respectively, indicating that most participants pass the financial literacy test.⁶

2.2 The survey evidence

We first consider investors’ biases, and then move on to analyze whether these biases tend to coexist within the same investor or spread across many investors in a mutually exclusive way.

2.2.1 Are retail investors rational or biased (or both) when trading stocks?

Table 2 presents the distribution of responses to survey questions. For each question, we score responses on a 1-5 scale (1=most negative; 5=most positive), and report the mean and median scores, the percentage of responses scored 4 or 5, and the difference between this percentage and that of responses scored 1 or 2.

⁵We also asked participants to indicate the industry in which they are currently employed (or were most recently employed). The top three industries are “Technology/Information Technology” (83 participants), “Finance/Banking/Insurance” (68), and “Manufacturing/Engineering” (55).

⁶Of 481 survey participants, 51 answered either the first or the second question (or both) incorrectly. We have verified that excluding these participants does not change our main results.

A. Fundamentals-based trading

Panel A of Table 2 indicates that most retail investors trade for neoclassical reasons. Specifically, 75.7% of participants respond “likely” or “very likely” to the question: “How likely are you to trade stocks based on a fundamental analysis of a firm (e.g., using past financials or a cash flow model)?” 64.9% respond “likely” or “very likely” to the question: “How likely are you to trade stocks because you need to rebalance/diversify your portfolio?” 74.2% “agree” or “strongly agree” to the statement: “One of the reasons I buy certain stocks is because I receive positive information about them from public sources (e.g., earnings announcements).” We also perform a *Z*-test to show that these percentages are significantly higher than those for negative responses (i.e., responses scored 1 or 2).

B. Overconfidence

Panel A of Table 2 indicates that a substantial fraction of retail investors tend to be overconfident. Specifically, 51.6% of participants respond “likely” or “very likely” to the question: “When you make investments in the stock market, how likely do you believe your investment returns will be above the market average over the next 12 months?” Participants appear more modest when comparing themselves to their peers: Only 26% rate their ability to pick winning stocks as “much better than average” or “slightly better than average.” Both of the above percentages are significantly higher than those for negative responses (i.e., responses scored 1 or 2).

C. Affect heuristic

Panel C of Table 2 indicates that retail investors can be influenced by affect heuristics. Specifically, 45.9% of participants “agree” or “strongly agree” to the statement: “When I trade stocks, my decisions are influenced by my perceptions of and familiarity with the company’s products.” The same percentage “agree” or “strongly agree” with the statement: “When I trade stocks, I tend to invest in companies that share my values and principles.” Again, we find that these percentages are significantly higher than those for responses scored 1 or 2.

D. Gambling

Panel D of Table 2 indicates that a substantial fraction of retail investors exhibit gambling propensity. We consider two questions that capture different aspects of gambling

behavior. The first question relates to viewing stocks as lotteries: “Do you agree with the following statement? When trading stocks, I tend to view them like lotteries; I am comfortable accepting small losses if they offer the chance of a big gain.” 56% of participants “agree” or “strongly agree” to this statement.⁷ The second question relates to the excitement and thrill of trading: “Do you agree with the following statement? When I trade stocks, I enjoy the excitement and thrill.” 47.6% “agree” or “strongly agree” to this statement. These percentages remain significantly higher than those for negative responses (i.e., responses scored 1 or 2).

Taken together, our analysis here shows that while most retail investors trade for rational reasons, they also exhibit various behavioral biases, such as overconfidence, affect heuristics, and gambling propensity, when trading.

2.2.2 Coexistence or segregation of rational trading and behavioral biases?

Do rational trading and behavioral biases coexist in the same investors, or are they segregated across different groups? We investigate this question in what follows.

Note that for each of the survey questions listed in Table 2 on rational trading, overconfidence, the affect heuristic, and gambling propensity, we score responses on a 1-5 scale (1=most negative; 5=most positive). Table 3 reports the pair-wise correlation coefficients among those scores. Columns 1–3 show that the scores on questions about rational trading (R1–R3) are significantly positively correlated with those on overconfidence (O1–O2) and affect heuristics (A1–A2). These scores are also significantly correlated with those on the excitement/thrill question (G2), though their correlation with those on the lotteries question (G1) is weaker both statistically and economically. The evidence here indicates that retail investors with high scores on rational trading also tend to have high scores on overconfidence, the affect heuristic, and gambling propensity—particularly the aspect related to excitement and thrill. This indicates quasi-rationality, which is a feature of our model.

⁷Lease, Lewellen, and Schlarbaum (1974), in their survey of individual investors, also find support for the notion that individual investors enjoy trading. Our focus here is somewhat more of the emotions generated by the lottery aspect of trading, rather than simple enjoyment. In a survey of retail investors, Dhar and Goetzmann (2006) report that more than 25% of investors view stock market investing as a hobby. Grinblatt and Keloharju (2009) provide empirical evidence that sensation-seeking personalities (e.g., those who get speeding citations) may get a thrill from the act of trading.

Columns 4–9 of Table 3 show that the scores on questions about overconfidence (O1–O2), affect heuristic (A1–A2), and gambling propensity (G1–G2) are significantly positively correlated. The evidence here indicates that retail investors with high scores on one bias also tend to have high scores on other behavioral biases.

Taken together, our analysis here suggests that various behavioral biases tend to coexist within the same retail investors. The preceding results provide strong motivation for our theoretical analysis to follow.

3 A Conceptual Framework

In this section, we present a model together with empirical implications that are motivated using the model’s analysis. The setting examines the joint effects of gambling propensity, affect heuristic, and overconfidence, which causes skepticism towards public information signals.

3.1 The economic setting

We now present the structure of our model, which consists of two dates, 0 and 1, and two classes of agents: rational, and biased (behavioral). The rational agents represent the arbitrage sector.

3.1.1 Assets and information

There are J stocks. At Date 1, the j ’th ($j = 1, \dots, J$) stock pays a liquidating cash flow of

$$V_j = \bar{V}_j + \ell_j F + (\theta_j + \xi_j),$$

where $\bar{V}_j$ is a positive constant denoting the unconditional mean, ℓ_j is a constant parameter denoting the loading on a common factor F , and θ_j and ξ_j denote the firm-specific cash flows. The random variables F , θ_j , and ξ_j are independent of each other. F (θ_j) follows a normal distributions with mean zero and variance ν_F (ν_{θ_j}). The ξ_j follow a skewed normal distribution with mean zero, variance ν_{ξ_j} , and skewness κ_j . This distribution allows us to build in skewness preference in our empirical implications, as in Kumar (2009). For simplicity, we assume that the per capita supply of each stock is unity, as a normalization. There is also a risk-free asset with a constant gross rate of return $R_f > 1$.

At Date 0, a public signal about the common factor, $\tau = F + \zeta$, is released, where the noise term ζ is drawn from a normal distribution with mean zero and variance ν_ζ . Also, a public signal about the j 'th stock's firm-specific cash flow, $s_j = \theta_j + \epsilon_j$, is released, where the noise term ϵ_j is drawn from a normal distribution with zero mean and variance ν_{ϵ_j} .

3.1.2 Investors

A continuum of investors with mass unity trade at Date 0, and consume at Date 1. Each investor is an atomistic price-taker. There are two types of investors: a mass η of investors with overconfidence, affect heuristic, and gambling propensity (or simply, *OAG* investors), and a mass $1 - \eta$ of rational investors. $\eta \in (0, 1]$ is a positive constant.

A. *OAG* investors

We assume that *OAG* investors are utility-maximizers and trade based on fundamentals, but are overconfident. The form of overconfidence we used based on [Odean \(1998\)](#) and [Luo, Subrahmanyam, and Titman \(2021\)](#), in that these investors skeptical about the quality of information they do not produce themselves. Specifically, such investors are overly attached to their prior cash flow expectation relative to a rational Bayesian, so that they underestimate the precision of public information. Thus, in assessing the public signal about the common factor, $\tau = F + \zeta$, they believe that ζ has a larger variance $\rho\nu_\zeta$ than the actual variance ν_ζ , where $\rho > 1$ is a constant parameter representing the scale of the overconfident bias. Denote the unbiased (skeptical) belief about the variance of τ as $\nu_\tau = \nu_F + \nu_\zeta$ ($\hat{\nu}_\tau = \nu_F + \rho\nu_\zeta$). *OAG* investors also underestimate the precision of the public signal about the firm-specific cash flow, $s_j = \theta_j + \epsilon_j$, in that they believe that ϵ_j has a larger variance $\rho\nu_{\epsilon_j}$ than the actual variance ν_{ϵ_j} . We denote the unbiased (skeptical) belief about the variance of s_j as $\nu_{s_j} = \nu_{\theta_j} + \nu_{\epsilon_j}$ ($\hat{\nu}_{s_j} = \nu_{\theta_j} + \rho\nu_{\epsilon_j}$).⁸

As in [Friedman and Heinle \(2016\)](#), *OAG* investors perceive that the j 'th stock produces

⁸In the Internet Appendix, we consider two variations of our setting here. First, in Section [IA.2](#), we consider a setting in which *OAG* investors underestimate the precision of each firm-specific public signal s_j to a different extent (i.e., ρ is not identical in the cross section). Second, in Section [IA.3](#), we consider a setting with the traditional form of overconfidence (i.e., the informed investors over-assess the precision of an additional private signal they receive, as in [Daniel, Hirshleifer, and Subrahmanyam 1998](#)). While both cases do not permit analytic solutions, we use numerical analysis to show that our reasoning still holds. Further, our reasoning also applies when the uninformed underassess the precision of information signals, or fail to condition on market prices ([Hong and Stein 1999](#); [Eyster, Rabin, and Vayanos 2019](#)). However, such models are also complex, and our investigation reveals that they have no analytic solutions.

an extra non-monetary payoff A_j beyond the actual level V_j . This reflects the idea that the stock evokes positive or negative emotions. This affect heuristic can arise from brand perceptions and loyalty (Schoenbachler, Gordon, and Aurand 2004; Frieder and Subrahmanyam 2005) and from societal norms against “sin” companies such as alcohol, tobacco, and gaming companies (Geczy, Stambaugh, and Levin 2005; Hong and Kacperczyk 2009). In this setting, A_j denotes the strength and direction of the affect heuristic. If A_j is positive (negative), then affect investors have a positive (negative) emotional attachment to the stock. Let X_{ij} denote the position of the i 'th *OAG* investor in the j 'th stock. Let W_{i1} denote the investor's final wealth at Date 1. The investor perceives the final wealth to be:

$$W_{i1}^A = W_{i1} + \sum_{j=1}^J (X_{ij} A_j).$$

OAG investors also obtain direct consumption benefits from their trading/holdings. Denote $X_i = \{X_{ij} : j = 1, \dots, J\}$. Let $C_G(X_i)$ be the extra benefit of holding stocks derived from non-wealth-related considerations. We define $C_G(X_i)$ as follows:

$$C_G(X_i) = 0.5 \sum_{j=1}^J (G_j X_{ij}^2),$$

where G_j is a positive constant representing investors' gambling propensity in the j 'th stock. In this specification, we model the idea that increasing the scale of the stock position increases the excitement derived from gambling in financial markets (Dorn and Sengmueller 2009). Based on this notion, the greater the holdings (in absolute terms), the higher the utility derived from investing. Therefore, we can think of this type of gambling propensity as a “betting-big” preference. Note that if G_j is high relative to γ (risk aversion), the investor, in effect, becomes a risk seeker, so there is no interior optimum for risky asset positions. We assume that the gambling propensity G_j is at a moderate level, so that there is indeed an interior optimum for the investor's demand for the j 'th stock.

The i 'th *OAG* investor has a mean-variance utility function over the perceived final wealth at Date 1, W_{i1}^A ; that is,

$$U_{OAG}(W_{i1}^A, X_i) = \hat{E}(W_{i1}^A) - 0.5\gamma\hat{\text{Var}}(W_{i1}^A) + C_G(X_i),$$

where $\hat{E}()$ and $\hat{\text{Var}}()$ indicate taking expectations and variance, respectively, based

on the investor's biased beliefs, and γ is a positive constant representing the risk-aversion coefficient.

B. Rational investors

Rational investors hold unbiased beliefs about the variances ν_ζ and ν_{ϵ_j} , and do not possess the affect and gambling biases. The i 'th rational investor has a mean-variance utility function over the final wealth at Date 1, W_{i1} ; that is,

$$U(W_{i1}) = E(W_{i1}) - 0.5\gamma\text{Var}(W_{i1}).$$

3.1.3 Vector and matrix notations

We use the following vector and matrix notations:

- $\bar{V}$, representing the mean cash flows, is a $J \times 1$ vector, where the j 'th ($j = 1, \dots, J$) element equals $\bar{V}_j$. ℓ , representing the loadings, is a $J \times 1$ vector, where the j 'th element equals ℓ_j . $\theta(\xi)$, representing the firm-specific cash flows, is a $J \times 1$ vector, where the j 'th element equals $\theta_j(\xi_j)$; its variance-covariance matrix $\nu_\theta(\nu_\xi)$ is a $J \times J$ diagonal matrix, where the j 'th diagonal element equals $\nu_{\theta_j}(\nu_{\xi_j})$.

The cash flow can be expressed in vector form as $V = \bar{V} + \ell F + (\theta + \xi)$.

- s , representing the information signals, is a $J \times 1$ vector, where the j 'th element equals s_j . Its variance-covariance matrix based on unbiased (skeptical) beliefs, $\nu_s(\hat{\nu}_s)$, is a $J \times J$ diagonal matrix, where the j 'th diagonal element equals $\nu_{s_j}(\hat{\nu}_{s_j})$.
- P , representing the prices, is a $J \times 1$ vector, where the j 'th element equals P_j . $\mathbf{1}$, representing the supplies, is a $J \times 1$ vector, where the j 'th element equals 1. X_i , representing the i 'th investor's demands, is a $J \times 1$ vector, where the j 'th element equals X_{ij} .
- A , representing the affect parameters, is a $J \times 1$ vector, where the j 'th element equals A_j . G , representing the gambling propensity, is a $J \times J$ diagonal matrix, where the j 'th diagonal element equals G_j .

OAG investors perceive the payoffs to be $A + V$. The direct utility of the i 'th OAG investor's positions in the risky assets is denoted by $C_G(X_i) = 0.5X_i'GX_i$.

3.2 The equilibrium

In this section, we determine the equilibrium of the setting described in Section 3.1. All proofs, unless otherwise stated, are in Appendix A. Define the following parameters:

$$\begin{aligned}\Delta &\equiv \frac{\nu_F}{\hat{\nu}_\tau} - \frac{\nu_F}{\nu_\tau}, & \hat{\nu}_{F|\tau} &\equiv \nu_F - \frac{\nu_F^2}{\hat{\nu}_\tau}, & \nu_{F|\tau} &\equiv \nu_F - \frac{\nu_F^2}{\nu_\tau} \\ \Omega &\equiv \nu_\theta \hat{\nu}_s^{-1} - \nu_\theta \nu_s^{-1}, & \hat{\nu}_{\theta|s} &\equiv \nu_\theta - \nu_\theta^2 \hat{\nu}_s^{-1}, & \text{and } \nu_{\theta|s} &\equiv \nu_\theta - \nu_\theta^2 \nu_s^{-1};\end{aligned}\quad (1)$$

further,

$$\begin{aligned}\phi_{OAG} &\equiv \ell \ell' \hat{\nu}_{F|\tau} + \hat{\nu}_{\theta|s} + \nu_\xi - G/\gamma, & \phi &\equiv \ell \ell' \nu_{F|\tau} + \nu_{\theta|s} + \nu_\xi, & \text{and} \\ \Phi &\equiv \eta \phi_{OAG}^{-1} + (1 - \eta) \phi^{-1}.\end{aligned}\quad (2)$$

We obtain the following theorem.

Theorem 1 *In equilibrium:*

(i) *Stock prices are given by:*

$$P = \frac{1}{R_f} \left[\bar{V} + \ell \frac{\nu_F}{\nu_\tau} \tau + \nu_\theta \nu_s^{-1} s + \Phi^{-1} [\eta \phi_{OAG}^{-1} (A + \ell \Delta \tau + \Omega s) - \gamma \mathbf{1}] \right].$$

(ii) *Each OAG and rational investor's demands for the stocks are respectively given by:*

$$\begin{aligned}X_{OAG} &= \frac{\phi_{OAG}^{-1}}{\gamma} \left(A + \bar{V} + \ell \frac{\nu_F}{\hat{\nu}_\tau} \tau + \nu_\theta \hat{\nu}_s^{-1} s - P R_f \right), \\ X_{Rational} &= \frac{\phi^{-1}}{\gamma} \left(\bar{V} + \ell \frac{\nu_F}{\nu_\tau} \tau + \nu_\theta \nu_s^{-1} s - P R_f \right).\end{aligned}$$

The term $\bar{V} + \ell \frac{\nu_F}{\nu_\tau} \tau + \nu_\theta \nu_s^{-1} s$ in the equilibrium price vector P represents the unbiased expectation of the final payoff V conditional on the public signals τ and s . The remaining terms reflect investors' behavior that goes beyond risk-reward considerations. Essentially a positive A (positive affect) implies a high mean price and vice versa, whereas overconfidence causes underweighting of the information signals in the realized price. Finally, a high G scales up the effect of the other (overconfidence and affect) biases. Thus, prices are the result of overconfidence, affect, and gambling interacting with each other.

The previous setting generally precludes analyzing the model in closed form. Therefore, in what follows, we first study a special case, where we are able to examine the equilibrium analytically. This allows us to obtain clear intuitions about the equilibrium. We subsequently perform a numerical analysis for the general case, and verify these intuitions.

3.2.1 A simple case with a closed-form solution

We consider a simple economy where the variances of the firm-specific payoffs $\theta_j + \xi_j$ are identical in the cross-section of stocks (i.e., $\forall j \nu_{\theta_j} + \nu_{\xi_j} = \nu$), and signals about the firm-specific component θ_j, s_j , are uninformative (i.e., $\forall j \nu_{\epsilon_j} \rightarrow \infty$). We then obtain the following theorem:

Theorem 2 *In the simplified economy where firm-specific payoff variances are identical across firms, and there are no information signals about firm-specific payoffs, the following results hold:*

(i) *The equilibrium prices are given by:*

$$P = \frac{1}{R_f} \left[\bar{V} + \ell \frac{\nu_F}{\nu_\tau} \tau + \Phi^{-1} [\eta \phi_{OAG}^{-1} (A + \ell \Delta \tau) - \gamma \mathbf{1}] \right].$$

(ii) *The demands of each OAG and rational investor are respectively given by:*

$$\begin{aligned} X_{OAG} &= \frac{\phi_{OAG}^{-1}}{\gamma} \left(A + \bar{V} + \ell \frac{\nu_F}{\hat{\nu}_\tau} \tau - P R_f \right), \\ X_{Rational} &= \frac{\phi^{-1}}{\gamma} \left(\bar{V} + \ell \frac{\nu_F}{\nu_\tau} \tau - P R_f \right). \end{aligned}$$

Since the signal about the firm-specific payoff θ_j, s_j , is not informative in the simple economy, the prices and demands for stocks do not depend on s_j unlike in the general case (see Theorem 1). The compensation for risk is represented by the term associated with $\gamma \mathbf{1}$ in the price vector P . The other terms in P , which are related to the mass of OAG investors (η) directly and/or through Φ , are the result of agents' trading behaviors grounded in their overconfidence, affect, and gambling propensity.

Specifically, due to overconfidence, OAG investors underestimate the precision of the signal τ (i.e., $\rho > 1$ and therefore $\hat{\nu}_\tau > \nu_\tau$). This underreaction is reflected in the term $\Delta < 0$ in the price vector P . Due to affect heuristics, these investors obtain an additional component A in their payoff, and their demand for a given stock increases if the affect parameter A_j for that stock (i.e., the j 'th element of the vector A) is higher. This tendency to demand more of a stock with a higher A_j value contributes to a higher equilibrium price for that stock on average. Finally, due to the gambling propensity scales up the effects of other (overconfidence and affect) biases on stock prices. The influence of gambling on stock prices is captured by the terms ϕ_{OAG} and Φ in the pricing equation.

We proceed below to analyze the influence of investors on turnover, the co-movement of stock returns with the market, underreaction to public information, and the risk-adjusted return. In the remainder of this section, we assume that we are in the economy described within Theorem 2. We further make a technical assumption that in this simple economy, the factor payoff exhibits sufficiently lower volatility compared to the firm-specific payoff (i.e., $\nu_F^{-1}\nu$ is sufficiently high). This assumption further allows us to conduct an analytical examination of the equilibrium.

A. Turnover

We first consider stock turnover. From Theorem 2, the demands of each *OAG* and rational investor for the j 'th stock, denoted by $X_{OAG,j}$ and $X_{Rational,j}$, respectively, are simply the j 'th elements of the vectors X_{OAG} and $X_{Rational}$. Let $\mathbf{1}_j$ be a $J \times 1$ vector where the j 'th element equals 1 and the other elements equal 0. We can then write:

$$X_{OAG,j} = \mathbf{1}_j' X_{OAG} \quad \text{and} \quad X_{Rational,j} = \mathbf{1}_j' X_{Rational}.$$

Suppose that each of the two investor types respectively starts with an endowment of $Y_{OAG,j}$ and $Y_{Rational,j}$ shares of the stock. The expected turnover of the j 'th stock is given by half of the sum of the absolute differences between each type of investor's demand for that stock and their initial endowment:

$$E(T_j) = 0.5 [\eta E(|X_{OAG,j} - Y_{OAG,j}|) + (1 - \eta) E(|X_{Rational,j} - Y_{Rational,j}|)]. \quad (3)$$

Note that our static setting can be interpreted as the reduced form of a steady-state setting, where investors begin Date 0 with positions equal to the ex-ante means of their demands (i.e., $\forall j Y_{OAG,j} = E(X_{OAG,j})$ and $Y_{Rational,j} = E(X_{Rational,j})$) as a result of prior re-balancing. As new information arrives, trading occurs. Specifically, the expected turnover of the j 'th stock takes the following form:

$$E(T_j^*) = 0.5 [\eta E(|X_{OAG,j} - E(X_{OAG,j})|) + (1 - \eta) E(|X_{Rational,j} - E(X_{Rational,j})|)]. \quad (4)$$

We obtain the following result:

Proposition 1 *Suppose that investors begin with positions that are equal to the ex-ante means of their demands (i.e., $\forall j Y_{OAG,j} = E(X_{OAG,j})$ and $Y_{Rational,j} = E(X_{Rational,j})$).*

- (i) If there is no overconfidence (i.e., $\rho = 1$), then the expected turnover $E(T_j^*) = 0$.
- (ii) With overconfidence ($\rho > 1$), the expected turnover $E(T_j^*)$ increases in the gambling propensity G_j (assuming $\ell_j \neq 0$) with the cross-section. $E(T_j^*)$ also increases in the overconfidence parameter ρ .

In the proof of Proposition 1, we derive the following equations for the trades of *OAG* and rational investors:

$$X_{OAG,j} - E(X_{OAG,j}) = \psi_{OAG,j} \Delta\tau \quad \text{and} \quad X_{Rational,j} - E(X_{Rational,j}) = \psi_j \Delta\tau,$$

where the ψ 's are constant parameters. We see from the above expressions that the affect parameter A_j does not affect trade. The reason for this is that *OAG* investors overbuy or oversell depending on the level of the constant A_j . This affects the mean position $E(X_j)$. However, if investors start at the mean position, A_j does not induce any further trading.

Note that trade is triggered by the overconfidence bias (see also Odean 1998). Specifically, if investors assess the precision of the signal τ properly (i.e., if $\rho = 1$), then $\Delta = 0$. Thus, without overconfidence, even if there is affect investing and gambling, there is no trade. However, if *OAG* investors underestimate the precision of the signal τ (i.e., if $\rho > 1$), then $\Delta < 0$; trade occurs. In this case, *OAG* investors perceive that a good (bad) outside (public) signal τ is not that good (bad), so that the resulting high (low) stock prices cannot be justified; therefore, they sell (buy). In the cross-section, if a stock has a higher gambling propensity G_j , *OAG* investors sell (buy) more aggressively, amplifying trading activity. As ρ increases, *OAG* investors underestimate the precision of the signal τ to a greater extent, and sell (buy) based on τ to a greater extent. This further intensifies trading activity.

Of course, investors can start with positions that are not identical to the ex ante means of their demands. In this case, we define $\lambda_{XY,j}$ as endowment-driven trade, which represents the deviation of endowment Y_j from the ex ante mean $E(X_j)$; specifically:

$$\lambda_{XY,j} = 0.5 \left[\eta (|E(X_{OAG,j}) - Y_{OAG,j}|) + (1 - \eta) (|E(X_{Rational,j}) - Y_{Rational,j}|) \right].$$

It is straightforward to show that the expected turnover in Equation (3) is

$$E(T_j) \in [E(T_j^*) - \lambda_{XY,j}, E(T_j^*) + \lambda_{XY,j}];$$

this means that $E(T_j^*)$ (the component of expected turnover due to information alone), represents the mid-point between the lower and upper bounds of $E(T_j)$. We are not able to further analyze the expected turnover $E(T_j)$ in closed form; we investigate it through numerical analysis in Section 3.2.2.

B. Underreaction to public information

Using Theorem 2, we can express the j 'th stock's excess return (i.e., the return above the risk-free interest rate) as follows:⁹

$$r_j = \mathbf{1}'_j(V - PR_f) = \ell_j \left(F - \frac{\nu_F}{\nu_\tau} \tau \right) + \theta_j + \xi_j - \mathbf{1}'_j \Phi^{-1} \left[\eta \phi_{OAG}^{-1}(A + \ell \Delta \tau) - \gamma \mathbf{1} \right]. \quad (5)$$

Consider a public signal regarding the j 'th stock:

$$S_j = \mu s_j + (1 - \mu) \tau, \quad (6)$$

where $\mu \in (0, 1]$ is a constant parameter. This public signal has two components, related to the firm-specific and factor signal, s_j and τ , respectively. This hybrid-type structure accounts for the fact that any particular signal would typically contain information about both the common and firm-specific components of value. Note that in the simple economy considered here, s_j is assumed to be uninformative; we will allow s_j to be informative in the numerical study in Section 3.2.2.

We use Equations (5) and (6) to compute $\text{Cov}(r_j, S_j)$, which we use to measure post-information returns.¹⁰

Proposition 2 *There is underreaction to the public signal ($\text{Cov}(r_j, S_j) > 0$) if and only if there is an overconfidence bias (i.e., $\rho > 1$). Further, in the cross-section of stocks, $\text{Cov}(r_j, S_j)$ increases in the gambling propensity G_j (assuming that ℓ_j is positive).*

If OAG investors assess the precision of the signal factor τ correctly (i.e., $\rho = 1$), then stock prices respond to the signal, $S_j = \mu s_j + (1 - \mu) \tau$ (note that s_j is assumed to be uninformative here), in a way that precisely reflects the information conveyed by the announcement. This implies that without overconfidence, there is no misreaction to the

⁹As is standard in exponential-normal settings, we measure the return via the price change (viz. [Hong and Stein 1999](#)).

¹⁰[Luo, Subrahmanyam, and Titman \(2021\)](#) show that this covariance can be interpreted as the return on a long-short portfolio formed based on S_j .

signal. If, however, *OAG* investors underestimate the precision of the signal τ due to overconfidence (i.e., $\rho > 1$), then $\Delta < 0$, and therefore, $\text{Cov}(r_j, S_j) > 0$; in this case, there is underreaction. Proposition 2 describes how gambling affects this underreaction.¹¹ The intuition is as follows: Suppose the information signal τ is positive; this implies that the announcement $S_j = \mu s_j + (1 - \mu)\tau$ is also likely to be positive. Since *OAG* investors underestimate the precision of τ , they perceive that the information is not that good and cannot be justified by the stock prices. They sell the stocks; this causes the price underreaction. If a stock has a higher G_j , *OAG* investors will take a bigger short position; this causes a greater extent of price underreaction.

C. The risk-adjusted expected return

We represent the market excess return using the cross-sectional average of stock returns (see Equation (5)):

$$r_M = \frac{1}{J} \mathbf{1}'(V - PR_f) = \ell_M \left(F - \frac{\nu_F}{\nu_\tau} \tau \right) + \theta_M + \xi_M - \Psi_M \times \Delta\tau - A_M + \gamma \Sigma_M, \quad (7)$$

where

$$\begin{aligned} \ell_M &= \frac{1}{J} \mathbf{1}' \ell, \quad \theta_M = \frac{1}{J} \mathbf{1}' \theta, \quad \xi_M = \frac{1}{J} \mathbf{1}' \xi, \quad \Psi_M = \frac{1}{J} \mathbf{1}' \Phi^{-1} \eta \phi_{OAG}^{-1} \ell, \\ A_M &= \frac{1}{J} \mathbf{1}' \Phi^{-1} \eta \phi_{OAG}^{-1} A, \quad \text{and} \quad \Sigma_M = \frac{1}{J} \mathbf{1}' \Phi^{-1} \mathbf{1}. \end{aligned}$$

From Equations (5) and (7), we can express the expected excess returns of the j 'th stock and the market as follows:

$$E(r_j) = \mathbf{1}_j' \Phi^{-1} (\gamma \mathbf{1} - \eta \phi_{OAG}^{-1} A) \quad \text{and} \quad E(r_M) = \gamma \Sigma_M - A_M. \quad (8)$$

The expected return of the stock adjusted for beta is:

$$\alpha_j = E(r_j) - \beta_{jM} E(r_M), \quad (9)$$

where $\beta_{jM} = \text{Cov}(r_j, r_M) / \text{Var}(r_M)$ is computed from Equations (5) and (7).¹² We obtain the following result:

¹¹From Equations (5) and (6), we observe that the affect parameter A_j does not affect the drift measure $\text{Cov}(r_j, S_j) > 0$. The reason is that the affect parameter A_j decreases the mean level of r_j , but does not affect its covariance with S_j .

¹²For convenience, our model assumes only one risk factor. However, the model can be easily extended to include multiple risk factors using the technique in [Luo, Subrahmanyam, and Titman \(2021\)](#).

Proposition 3 (i) *If overconfidence, affect investing, and gambling are absent (i.e., $\rho = 1$ and $A_j = G_j = 0 \forall j$), then the risk-adjusted expected return $\alpha_j = 0$.*

(ii) *If overconfidence, affect investing, and gambling are present (i.e., $\rho > 1$ and $\exists j$ such that $A_j \neq 0$ and $G_j > 0$), then in the cross-section of stocks, the derivative of α_j with respect to the affect parameter A_j is negative. The absolute magnitude of this derivative increases in gambling propensity G_j .*

Proposition 3 shows that the risk-adjusted expected return α_j equals zero in the benchmark case where the overconfidence bias, affect investing, and gambling are absent. However, when these biases are present, $\alpha_j \neq 0$ and depends on the affect and gambling parameters, A_j and G_j . To obtain further insight, consider stocks with a relatively high affect parameter A_j . OAG investors have an abnormally high demand for such stocks, causing them to become overpriced compared to others. This leads to a low risk-adjusted expected return α_j . For a higher G_j , gambling scales up the rise in the stock price P_j as well as the decrease in α_j . A reverse intuition holds for negative A_j .

3.2.2 The general case: Numerical illustration

In this section, we move away from the special case of the previous section, which means we lose analytical solutions. We examine the general case using numerical analysis. We use this analysis to verify the implications of the special-case equilibrium for turnover, stock return co-movement with the market, the post-public-announcement drift, and risk-adjusted expected returns.

A. Turnover

We consider an economy with $J = 200$ stocks, where the G_j values are evenly distributed on the support $[0, 0.5]$, with corresponding range for A_j being $[-2, 2]$. The other parameter values are $\gamma = 2$ and $\eta = 0.5$; $\forall j \ell_j = 1$, $\nu_{\theta_j} = 1$, $\nu_{\epsilon_j} = \nu_{\theta_j}/2$, and $\nu_{\xi_j} = 0.01$; $\nu_F = 0.01$ and $\nu_\zeta = \nu_F/2$. The overconfidence parameter ρ takes values from 1 to 9.¹³ We

¹³Our value for risk aversion, $\gamma = 2$, is the same as that used in Leland (1992) and Holden and Subrahmanyam (2002). We assume a significant mass of each type of investor, with $\eta = 0.5$. The values of $\ell_j = 1$ and $\nu_{\theta_j} = 1$ for all j are normalization constants. We choose $\nu_{\xi_j} = 0.01$ (with $SD(\xi_j) = 0.1$), so that a small but significant component of the firm-specific cash flow is skewed. Next, we use $\nu_F = 0.01$ (with $SD(F) = 0.1$), so that the common factor is less volatile than the firm-specific cash flow. We set $\nu_{\epsilon_j} = \nu_{\theta_j}/2$ and $\nu_\zeta = \nu_F/2$ to indicate a significant magnitude of noise in the signals s_j and τ . Our results are generally robust to different parameter values.

can use Theorem 1 to obtain the demand for the j 'th stock by each *OAG* and rational investor, denoted by $X_{OAG,j}$ and $X_{Rational,j}$, respectively, which are the j 'th elements of the vectors X_{OAG} and $X_{Rational}$. We can then use Equation (3) to compute the expected turnover of the j 'th stock. In Figure 1, we plot the expected turnover $E(T_j)$ for each stock as a function of gambling propensity G_j , for different values of overconfident investors' overconfidence ρ ranging from 1 to 9.¹⁴ As in Proposition 1, we assume here that each type of investors' endowments equal the ex ante means of their optimal demands (i.e., $\forall j, Y_{OAG,j} = E(X_{OAG,j})$ and $Y_{Rational,j} = E(X_{Rational,j})$); in this case, the turnover is not affected by the affect parameter A_j .

Figure 1 supports findings from the previous analysis (see Proposition 1). Specifically, when overconfident investors correctly assess the precision of the signals (i.e., $\rho = 1$), no trading occurs. Conversely, if they underestimate the precision of the signals (i.e., $\rho > 1$), trading does occur, and an increase in the gambling propensity G_j leads to an increase in $E(T_j)$. Additionally, an increase in the overconfidence parameter ρ results in an increase in the expected turnover $E(T_j)$. Our analysis also suggests that both the overconfidence bias and gambling play distinct roles in trading activity. Specifically, the overconfidence bias triggers trading, while gambling amplifies it. This implication is consistent with the findings of Liu et al. (2022), which suggest that overconfidence in having an information advantage and a preference for gambling are the primary drivers of trading.

If, unlike in Proposition 1, each type of investors' endowments do not equal the ex ante means of their optimal demands, then in the cross-section of stocks, turnover can also depend on the affect parameter A_j . Figure 2 considers two other scenarios for endowments. In Panel A, we assume that each investor's endowment equals the per capita supply (i.e., $\forall j, Y_{OAG,j} = Y_{Rational,j} = 1$), and in Panel B investor endowments are identically zero (i.e., $\forall j, Y_{OAG,j} = Y_{Rational,j} = 0$). We plot the expected turnover $E(T_j)$ for each stock as a function of the gambling propensity G_j and the affect parameter A_j . It is notable that the cross-sectional relationship between $E(T_j)$ and A_j is non-monotonic; $E(T_j)$ is higher for stocks with extreme positive/negative values of A_j . In other words, investors with strong positive/negative affect toward these stocks tend to trade them more actively. This heightened response drives them to buy or sell more intensely to reach their optimal

¹⁴This range is consistent with that of Odean (1998) (pp. 1909–10).

holdings, intensifying trading activity. The relationship between gambling and turnover also remains consistent with the previous analysis. Specifically, in the cross-section of stocks, the expected turnover $E(T_j)$ increases as gambling propensity G_j increases.

B. Underreaction to public signals

Using Theorem 1, we can express the realized excess return of the j 'th stock as

$$r_j = \mathbf{1}'_j(V - PR_f). \quad (10)$$

Recall that the public signal for the j 'th stock (see Equation 6) takes the following form:

$$S_j = \mu s_j + (1 - \mu)\tau,$$

where $\mu \in (0, 1]$ is a constant parameter. We can use r_j given in Equation (10) to compute the underreaction measure $\text{Cov}(r_j, S_j)$.

Figure 3 plots $\text{Cov}(r_j, S_j)$ for each stock as a function of gambling propensity G_j , for different levels of the overconfidence bias (ρ). We set $\mu = 0.8$ (our results are robust to different values of μ); the other parameters are the same as those used in the earlier figures. Confirming our previous analysis (Proposition 2), when OAG investors assess the precision of the signals properly (i.e., $\rho = 1$), we observe $\text{Cov}(r_j, S_j) = 0$ indicating no underreaction. However, if OAG investors underestimate the precision of the signals s and τ (i.e., $\rho > 1$), then underreaction arises, i.e., $\text{Cov}(r_j, S_j) > 0$, and an increase in the gambling propensity G_j leads to an increase in $\text{Cov}(r_j, S_j)$. We also observe from Figure 3 that if overconfident investors underestimate the precision of the signals to a greater extent (i.e., if ρ is higher), $\text{Cov}(r_j, S_j)$ is greater. This result aligns with the discussion following Proposition 2. Specifically, a higher ρ implies more underreaction, which, in turn, implies a greater return drift following public disclosures about fundamentals.

C. The (unconditional) risk-adjusted expected return

We represent the market excess return using the cross-sectional average of stock returns (see Equation 10):

$$r_M = \frac{1}{J} \mathbf{1}'(V - PR_f). \quad (11)$$

It follows from Equations (10) and (11) and Theorem 1 that the expected excess returns of the j 'th stock and the market can be expressed as

$$E(r_j) = \mathbf{1}'_j \Phi^{-1} (\gamma \mathbf{1} - \eta \phi_{OAG}^{-1} A), \text{ and } E(r_M) = \frac{1}{J} \mathbf{1}' \Phi^{-1} (\gamma \mathbf{1} - \eta \phi_{OAG}^{-1} A).$$

Note that these expected returns are unconditional, i.e., they do not condition on the public signals τ and s . We can compute the (unconditional) risk-adjusted expected returns of the stocks as

$$\alpha_j = E(r_j) - \beta_{jM} E(r_M),$$

where $\beta_{jM} = \text{Cov}(r_j, r_M) / \text{Var}(r_M)$ for each stock.

Figure 4 plots the risk-adjusted return α_j for each stock as a function of its gambling propensity G_j and affect parameter A_j . In line with our previous analysis (see Proposition 3), we observe that in the cross-section of stocks, α_j decreases as the affect parameter A_j increases. Additionally, the negative relationship between α_j and A_j becomes more pronounced when gambling propensity G_j is high.

3.3 Empirical implications

Based on our theoretical analyses, we formulate four main empirical implications which we test using available data for U.S. equities. We provide these implications below, along with references to the propositions and/or figures that support them:¹⁵

- (i) (Proposition 1 and Figures 1-2) In the cross-section of stocks, turnover increases in gambling propensity.
- (ii) (Proposition 2 and Figure 3) Underreaction to public information is more pronounced when gambling propensity is high.
- (iii) (Proposition 3 and Figure 4) The risk-adjusted return decreases in the affect heuristic; this negative relationship becomes more pronounced when gambling propensity is high.

¹⁵While Propositions 1-3 used for the implications are derived under the assumption that, after accounting for conditional information, the factor payoff is sufficiently less volatile than the firm-specific payoff, we have verified that these results hold for the parameter values used in the calibration in Section 3.2.2.

4 Empirical Analysis

We now test the empirical implications of our model for turnover, post-public-announcement drift, and risk-adjusted expected returns, using data on U.S. equities.

4.1 Data

We obtain our sample of common stocks traded on NYSE, NASDAQ, and AMEX from the CRSP database. We retrieve accounting information from the Compustat database. To avoid potential market microstructure issues, we exclude stock-months with prices below \$1 as of the end of the past month.¹⁶

For each stock-month, we compute the turnover (TO) as monthly share turnover as reported by CRSP, scaled by the number of outstanding shares at the end of the past month. To address NASDAQ double counting due to the recording of inter-dealer trades in turnover, we follow the method proposed by [Gao and Ritter \(2010\)](#) and divide the turnover of NASDAQ stocks by 2.0 before January 2001, by 1.8 for the rest of 2001, by 1.6 for 2002-2003, and leave it unchanged thereafter. We calculate the risk-adjusted return as the stock's excess return over the risk-free interest rate or the difference between the stock return and the benchmark-implied return in the month. We estimate our benchmark models, including the CAPM, the [Fama and French \(1993\)](#) and [Carhart \(1997\)](#) four-factor model (FFC4), and the [Fama and French \(2015\)](#) five-factor model (FF5), using at least 18 monthly returns in the past 36 months.¹⁷

We next use the quarterly report that is announced in the past three months to obtain two measures of public announcements for each stock-month.¹⁸ First, [Ball and Brown \(1968\)](#) and [Bernard and Thomas \(1989\)](#) find evidence that a company's stock price continues to drift in the direction of an earnings surprise. For stock-quarter q , we follow [Foster, Olsen, and Shevlin \(1984\)](#) to estimate for the stock (j)'s earnings per share (EPS) the regression $EPS_{j,q} = a + b \cdot EPS_{j,q-4} + \epsilon_{j,q}$ using at least 10 observations in the past 20 quarters. We compute the standardized unexpected earnings (SUE) for the stock-quarter as the difference between the actual EPS and the expected EPS based on the EPS in quarter $q-4$,

¹⁶Our empirical results are not significantly affected when we instead use a \$5 threshold for penny stocks.

¹⁷We obtain the market, size, and value factors through Wharton Research Data Services, and the five [Fama and French \(2015\)](#) factors from Kenneth French's website (<https://tinyurl.com/336hyekj>).

¹⁸For a quarterly report in Compustat, we use item RDQ , the reporting date, as the release date (see [Novy-Marx 2013](#)).

scaled by the standard deviation of the residuals from the regression, $SD(\epsilon_{j,q})$. Second, [Novy-Marx \(2013\)](#) finds evidence that stock returns exhibit predictability in the direction of profitability (specifically, firms with high announced gross margins generate significantly higher returns than firms with the opposite characteristic). For a stock-quarter, we compute *Profitability* as the ratio of a firm’s gross profits (revenues minus cost of goods sold) in the quarter to its assets at the beginning of the quarter.

We follow [Kumar \(2009\)](#) to identify a stock as having a high level of gambling propensity (*GP*) if the stock has a low price (i.e., “cheap bet,” which can be viewed as a low value of the ex ante mean price $\bar{V}_j$), high idiosyncratic volatility (i.e., a high variance of ξ_j in the model), and high idiosyncratic skewness (i.e., small probability of a huge reward; which is the skewness of ξ_j). Specifically, for each stock-month, from at least 90 daily data in the past 6 months, we compute the average stock price (*PRC*); we compute the idiosyncratic volatility (*IVOL*) and skewness (*ISKEW*) as, respectively, the standard deviation and the skewness of the residuals from the [Fama and French \(2015\)](#) five-factor model. If in the cross-section, the *PRC* is in the bottom three deciles, the *IVOL* is in the top three deciles, and the *ISKEW* is in the top three deciles, then $GP = 1$ for the stock-month equals 1; otherwise, $GP = 0$.

[Campbell and Keller \(2003\)](#) and [Grullon, Kanatas, and Weston \(2004\)](#) find evidence that a firm’s product market advertising increases brand visibility and attracts investor attention (see also [Chan, Lakonishok, and Sougiannis 2001](#); [Lou 2014](#)). We thus use a firm’s advertising expenditure in the product market as a proxy for the affect heuristic for a stock. We retrieve the annual advertising expense (*XAD*) from the Compustat database for the firm.¹⁹ For each stock-month from July of a year to June of the next year, we use the annual report in the past fiscal year to compute the growth of the advertising expense, *ADV*. For a fiscal year y , we compute for the stock j : $ADV_{j,y} = \ln(XAD_{j,y} + 1) - \ln(XAD_{j,y-1} + 1)$; we further de-mean this *ADV* by the cross-sectional industrial average *ADV*, and scaled the result by the cross-sectional standard deviation of the *ADV* in the industry.

¹⁹We ignore firm-years with missing *XAD* information because we are not able to tell whether the firm fails to report *XAD*, or its advertising expense is actually zero. We have also tried to exclude firm-years with advertising expenses below \$100,000, as suggested by [Lou \(2014\)](#). Our results remain robust to this exclusion.

In our empirical analyses, we also control for several firm characteristics. For each stock-month, ME is the stock's market value of equity (i.e., the stock price $\times$ the number of outstanding shares) as of the end of the past month; $Firm\ age$ is the number of months since the stock's first CRSP appearance as of the end of the past month. If the stock-month is in the period from July of a year to June of the next year, BM is the book-to-market ratio computed using the book equity as of the end of the past fiscal year, and the market value of equity as of the end of the past calendar year;²⁰ D/A is the stock's book debt (i.e., the sum of short-term and long-term debt) divided by total assets as of the end of the past fiscal year. $EVOLA$ is the earnings volatility of the stock computed as the standard deviation of EPS using at least 10 quarters in the past 20 quarters. ANA is the number of analysts who follow the firm and report forecasts to the I/B/E/S database in the past month; and $FDISP$ is the stock analysts' forecast dispersion, which is computed as the standard deviation of EPS forecasts reported by analysts in the I/B/E/S database in the past month. AT is the turnover-based Amihud (2002) illiquidity measure computed as the average of the ratio of the daily absolute return to daily turnover (see Brennan, Huh, and Subrahmanyam 2013; Lou and Shu 2017) using at least 90 daily data in the past six months.

Appendix B provides detailed definitions of the variables. Our sample period is from January 1977 to December 2024. To address extreme values, we winsorize all continuous variables (i.e., all variables except $Firm\ age$ and ANA) at the 1% and 99% levels,²¹ using each of their distributions every month. The exceptions are risk-adjusted returns, which are not winsorized.

Table 4 presents the time-series averages of the cross-sectional statistics of selected variables. The average turnover (TO) and stock return ($r_{j,t}$) are 11% and 1.1% per month, respectively. The means of the earnings surprise measure (SUE) and gross margins ($Profitability$) are 0.962 and 0.088, respectively. The typical (mean) market equity (ME) and firm age are \$3.013 billion and 181 months, respectively. Book-to-market (BM) and leverage (D/A) means are 0.802 and 0.233, respectively. The average EPS volatility ($EVOLA$) is \$0.52 per quarter. The means of analyst following (ANA) and EPS fore-

²⁰We follow Fama and French (1993) and require both the market equity and the book equity to be positive. Our empirical results still hold if we do not impose this requirement.

²¹We also try winsorizing at 0.5%-99.5% as a robustness check; our results continue to obtain.

cast dispersion ($FDISP$) are 1.827 and \$0.145, respectively. The average turnover-based Amihud (2002) illiquidity measure (AT) is 71.591.

4.2 Gambling and turnover

Implication (i) from Section 3.3 is that in the cross-section of stocks, turnover should increase in gambling propensity. We test this implication using the following regression:

$$TO_{j,t} = b_0 + b_1 \times GP_{j,t} + b_2 \times Controls + \epsilon_{j,t}. \quad (12)$$

The dependent variable $TO_{j,t}$ is the turnover of the j 'th stock in month t . GP equals 1 if in the past six months, the average stock price (PRC) is in the bottom three deciles and the idiosyncratic volatility ($IVOL$) and skewness ($ISKEW$) are both in the top three deciles in the cross-section, and 0 otherwise. We control for past stock returns in months $t-1$, $t-2$, and $t-12$ to $t-3$ ($r_{j,t-1}$, $r_{j,t-2}$, and $r_{j,t-12 \text{ to } t-3}$), market equity (ME), firm age, book-to-market ratio (BM), leverage (D/A), earnings volatility ($EVOLA$), the number of analysts following the firm and reporting forecasts (ANA), analyst forecast dispersion ($FDISP$), illiquidity (AT). We use past stock returns to capture possible trend-chasing (Hong and Stein 1999). According to Chordia, Huh, and Subrahmanyam (2007), firm size (i.e., market equity, ME), firm age, and book-to-market ratio (BM) proxy for a firm's visibility; earnings volatility ($EVOLA$) proxies for uncertainty about fundamental values; the number of analysts following the firm (ANA) proxies for the mass of informed agents; and leverage (D/A) and analysts' forecast dispersion ($FDISP$) proxy for differences of opinion. Note that by construction, gambling stocks (i.e., stocks with $GP = 1$) have low stock prices, and high volatilities and skewness; they likely have low liquidity. Therefore, we also control for illiquidity (AT).

We estimate Regression (12) using the Fama and MacBeth (1973) procedure and correct standard errors using the Newey-West method with up to three lags. Table 5 presents the results. We find consistent evidence that the coefficient on GP is significantly positive. Specifically, in Column 1, the GP coefficient is 3.925 (t -stat.= 6.46) after controlling for past stock returns, ME , firm age, BM , D/A , $EVOLA$, and AT . In Column 2, the GP coefficient is 2.065 (t -stat.= 5.8) after further controlling for ANA and $FDISP$. The latter coefficient suggests that the monthly turnover of the gambling stocks (i.e., $GP = 1$) is

higher than that of other stocks (i.e., $GP = 0$) by 2.065%, which corresponds to 18.8% of the mean turnover level (11% from Table 4).

Table 5 also presents additional evidence on turnover. Specifically, the coefficient on the past stock return $r_{j,t-12 \text{ to } t-3}$ is significantly positive, suggesting trend chasing or portfolio rebalancing. The coefficients on $\ln(\text{Firm age})$ and BM are significantly negative, indicating that young stocks and growth stocks have high turnover. Earnings volatility ($EVOLA$) commands a positive slope, suggesting that uncertainty about fundamental values increases turnover. The coefficient on the number of analysts following the firm (ANA) is significantly positive, evidencing analyst-induced trading. Leverage (D/A) and analysts' forecast dispersion ($FDISP$) are significantly positive, and the latter indicates that differences of opinion increase turnover. The coefficient on the illiquidity measure (AT) is significantly negative, which is consistent with the notion that it costs less to trade liquid stocks. These findings are in line with previous research on trading activity (e.g., Chordia, Huh, and Subrahmanyam 2007).

4.3 Gambling and the underreaction to public announcements

Implication (ii) from Section 3.3 is that underreaction to public signals is more pronounced when gambling propensity is high. As motivated in Section 4.1, we use the earnings surprise (SUE) as in Foster, Olsen, and Shevlin (1984) and gross margins ($Profitability$) as in Novy-Marx (2013) to test this implication.

4.3.1 Gambling and the post-earnings-announcement drift

We first use portfolio analysis to test the relation between gambling propensity and the post-earnings-announcement drift (PEAD). For month t , we divide the sample stocks into two equal groups based on SUE (estimated from the quarterly report announced in the past three months), and independently into two groups based on GP ; this leads to 2×2 portfolios. For each portfolio, we compute the return by weighting stocks in the portfolio equally; we then compute the excess return over the risk-free interest rate (Exret) and benchmark-adjusted returns based on the CAPM, the Fama and French (1993) and Carhart (1997) 4-factor model (FFC4), and the Fama and French (2015) 5-factor model (FF5).

Table 6 presents the portfolio results. Column 1 shows that the portfolio of high- SUE

stocks significantly outperforms the portfolio of low-*SUE* stocks by 48.4 basis points (bps) per month (t -stat.= 4.46), which is consistent with the PEAD documented by [Ball and Brown \(1968\)](#) and [Bernard and Thomas \(1989\)](#). Columns 2 and 3 show that while this outperformance is 142.9 bps (t -stat.= 7.4) among stocks with $GP = 1$, it is only 44.1 bps (t -stat.= 4.64) among stocks with $GP = 0$; the difference is significantly positive at 98.8 bps (t -stat.= 5.55). The evidence is similar in other columns where we use risk-adjusted returns. For example, Columns 8 and 9 shows that using FF5-*adjusted return*, this outperformance is still greater among stocks with $GP = 1$ than among stocks with $GP = 0$ by 88.9 bps (t -stat.= 4.81). Taken together, our portfolio analysis here shows that the PEAD is more pronounced when gambling propensity is high.

We then use regression analysis to test the relation between gambling propensity and the PEAD. Specifically, we use the following regression:

$$\begin{aligned} Risk\text{-}adjusted\ return_{j,t} = & b_0 + b_1 \times SUE_{j,t} + b_2 \times SUE_{j,t} \times GP_{j,t} \\ & + b_3 \times GP_{j,t} + b_4 \times Controls + \epsilon_{j,t}. \end{aligned} \quad (13)$$

The dependent variable *Risk-adjusted return* _{j,t} is either the j 'th stock's excess return over the risk-free interest rate, or the difference between the stock return and the benchmark-implied return in month t . We control for past stock returns ($r_{j,t-1}$, $r_{j,t-2}$, and $r_{j,t-12}$ to $t-3$), market equity (ME), book-to-market ratio (BM), and illiquidity (AT).

Table 7 presents results from the Fama-MacBeth estimation of Regression (13). The evidence confirms that the PEAD is more pronounced when the gambling propensity (GP) is high. For example, consider the FF5-*adjusted return* in Columns 7 and 8. In Column 7, both the coefficient on *SUE* (0.086, t -stat.= 6.46) and the coefficient on *SUE* $\times$ *GP* (1.111, t -stat.= 4.70) are significantly positive. We find consistent evidence in Column 8, where we control for past stock returns, *ME*, *BM*, and *AT*. Particularly, both the coefficient on *SUE* (0.116, t -stat.= 10.30) and the coefficient on *SUE* $\times$ *GP* (1.069, t -stat.= 4.39) are significantly positive. The evidence is similar in other columns of Table 7 where we use the excess return and in turn, risk-adjusted returns based on the CAPM and FFC4 models as the dependent variable.

Table 7 also presents evidence of the short-term reversal effect (i.e., the coefficient on $r_{j,t-1}$ is significantly negative) and the size effect (i.e., the coefficient on $\ln(ME)$ is signif-

icantly negative). We also find evidence of momentum and value effects (e.g., Column 2 shows that the coefficients of the excess return on $r_{j,t-12 \text{ to } t-3}$ and BM are significantly positive).

4.3.2 Gambling and the post-profitability-announcement drift

We continue to use regression analysis to test the relation between gambling propensity and the post-profitability-announcement drift.²² Specifically, we use the following regression:

$$\begin{aligned} \text{Risk-adjusted return}_{j,t} = & b_0 + b_1 \times \text{Profitability}_{j,t} + b_2 \times \text{Profitability}_{j,t} \times GP_{j,t} \\ & + b_3 \times GP_{j,t} + b_4 \times \text{Controls} + \epsilon_{j,t}. \end{aligned} \quad (14)$$

For the j 'th stock in month t , we use the quarterly report announced in the past three months to compute the gross margins (*Profitability*). We continue to control for past stock returns ($r_{j,t-1}$, $r_{j,t-2}$, and $r_{j,t-12 \text{ to } t-3}$), market equity (ME), book-to-market ratio (BM), and illiquidity (AT).

Table 8 presents results from the Fama-MacBeth estimation of Regression (14). The evidence is consistent with the notion that the post-profitability-announcement drift is more pronounced when the gambling propensity (GP) is high. For example, consider the FF5-adjusted return in Columns 7 and 8. In Column 7, both the coefficient on *Profitability* (2.979, t -stat.= 6.46) and the coefficient on *Profitability* $\times$ GP (6.785, t -stat.= 4.77) are significantly positive. We find consistent evidence in Column 8, where we control for past stock returns, ME , BM , and AT . Particularly, both the coefficient on *Profitability* (3.438, t -stat.= 7.22) and the coefficient on *Profitability* $\times$ GP (7.027, t -stat.= 4.53) are significantly positive. The evidence is similar in other columns of Table 8 where we use the excess return and in turn, risk-adjusted returns based on the CAPM and FFC4 models as the dependent variable.

4.4 Gambling, affect investing, and risk-adjusted expected returns

Implication (iii) from Section 3.3 is that in the cross-section of stocks, risk-adjusted expected returns should decrease in the affect heuristic, and this negative relationship should be more pronounced when gambling propensity is high.

²²We also use a portfolio method to verify the results here and in what follows and find confirming evidence in the Internet Appendix (see Tables IA.1 and IA.2).

Recall from Section 4.1 that we measure the affect heuristic for a stock using ADV , the industry-adjusted growth of the advertising expense. We test the effect of gambling propensity (GP) on the relation between risk-adjusted return and ADV using the following regression:

$$\begin{aligned} Risk\text{-adjusted return}_{j,t} = & b_0 + b_1 \times ADV_{j,t} + b_2 \times ADV_{j,t} \times GP_{j,t} \\ & + b_3 \times GP_{j,t} + b_4 \times Controls + \epsilon_{j,t}. \end{aligned} \quad (15)$$

If month t is in the period from July of a year to June of the next year, ADV is the industry-adjusted growth of the advertising expense computed using the annual report in the past fiscal year. We control for the earnings surprise (SUE) and gross margins ($Profitability$), and their interactions with GP , as suggested by the empirical analysis in Section 4.3, along with past stock returns ($r_{j,t-1}$, $r_{j,t-2}$, and $r_{j,t-12}$ to $t-3$), market equity (ME), book-to-market ratio (BM), and illiquidity (AT).

Table 9 presents the results from the Fama-MacBeth estimation of Regression (15). The evidence indicates that the negative relation between risk-adjusted returns and ADV is more pronounced when the gambling propensity (GP) is high. For example, consider the FF5-adjusted return in Columns 10-12. Column 10 shows that both the coefficient on ADV (-0.047 , $t\text{-stat.} = -1.72$) and the coefficient on $ADV \times GP$ (-0.396 , $t\text{-stat.} = -1.67$) are significantly negative. In Column 11 where we control for SUE and $SUE \times GP$, along with past returns, ME , BM , and AT , the coefficient on ADV (-0.008) is still negative though no longer statistically significant, the coefficient on $ADV \times GP$ (-0.652 , $t\text{-stat.} = -2.16$) remains significantly negative. In Column 12 where we control for $Profitability$ and $Profitability \times GP$ instead, the coefficient on ADV (-0.051) is again negative though insignificant, the coefficient on $ADV \times GP$ (-0.540 , $t\text{-stat.} = -2.06$) remains significantly negative. We note further that consistent with Tables 7 and 8, both the PEAD and the profitability effect are stronger when gambling propensity is high. Specifically, Column 11 shows that both SUE and $SUE \times GP$ have significantly positive coefficients, while Column 12 shows that both $Profitability$ and $Profitability \times GP$ have significantly positive coefficients. Similar patterns are observed in other columns where we use the excess return and in turn, risk-adjusted returns based on the CAPM and FFC4 models as the dependent variable.

5 Extensions, Limitations, and Further Discussion

In our theoretical approach, we make a number of modeling choices, and use some subjectivity in choosing our empirical proxies. Although our modeling choices are rooted in survey evidence, a discussion of these modeling decisions is desirable.

5.1 Theory

First, the behavioral literature considers deviations from the [Von Neumann and Morgenstern \(1944\)](#) expected utility paradigm beyond our treatment. For example, prospect theory ([Kahneman and Tversky 1979](#)) involves valuing wealth increases and decreases separately, and there are versions of utility theory where skewness is positively valued ([Kraus and Litzenberger 1976](#); [Mitton and Vorkink 2007](#)). In these cases, the investor still values assets only for their monetary aspect. Although insights from this branch of literature are valuable, our goal is to introduce a different category of problem where assets provide direct consumption benefits beyond monetary wealth considerations (viz. our opening quotes from [Black 1975](#) and [Fama and French 2007](#)). We focus on this alternative to utility-of-wealth for parsimony, but an important area of research would seem to be the consideration of how prospect theory and skewness preference combine with gambling and affect considerations.

We also note that many behavioral biases involve deviations from rational expectations. For example, the extrapolation bias ([Lakonishok, Shleifer, and Vishny 1994](#)) involves a naïve forecast that the future will match the past, and in anchoring ([Tversky and Kahneman 1974](#)), the agent deviates insufficiently from initial beliefs. We follow [Odean \(1998\)](#) in our focus on the pervasive overconfidence bias (viz. [De Bondt and Thaler 1985](#)) as our departure from rational beliefs. In a sense, this bias is the baseline with respect to which we measure the impact of gambling and the affect heuristic. We conjecture that our basic insight that gambling amplifies “overtrading,” and thus scale up the impact of biases, would continue to obtain in a model with additional perturbations relative to neoclassical approaches.

5.2 Empirical proxies

Note that overconfidence plays a key role in turnover ([Proposition 1](#)) and in the underreaction to public information ([Proposition 2](#)). The reader may wonder if proxies for over-

confidence could be used to test for this divergence. However, for the U.S., it is challenging to identify effective overconfidence proxies that are not also endogenous (e.g., trading volume itself, as analyzed in [Odean 1998](#) and [Statman, Thorley, and Vorkink 2006](#)). A possible variant of this study would be to consider individual investors' overconfidence scores via surveys and relate them to quantities like the post-public-announcement drift. There is evidence that such scores may be available via surveys for countries other than the U.S. ([Grinblatt and Keloharju 2009](#); [Liu et al. 2022](#)).

In our model, overconfidence implies underreaction to outside information such as public signals ([Odean 1998](#); [Luo, Subrahmanyam, and Titman 2021](#)). This leads to the issue of what information signal is empirically reasonable. We focus on two of the most prominent underreaction phenomena. The first is the post-earnings drift ([Bernard and Thomas 1989](#)). The second is the return continuations following gross profit revelations ([Novy-Marx 2013](#)). We use gross profits in addition to earnings surprises because of some controversy whether post-earnings drift has attenuated in recent years ([Martineau 2022](#); [Hirshleifer, Peng, and Wang 2025](#)). [Ball et al. \(2016\)](#) confirm the robustness of the profitability anomaly. [Bouchaud et al. \(2019\)](#) show that this anomaly arises due to investor underreaction. [Subrahmanyam \(2024\)](#) shows that profitability is the main anomaly that survives in more recent years. Although we use these two phenomena in our study for parsimony, other phenomena may also be considered.

Finally, inspired by [Grullon, Kanatas, and Weston \(2004\)](#), we use advertising expense as our proxy for brand equity, and in turn, the strength of the affect heuristic. The “sin” status of stocks ([Hong, Lim, and Stein 2000](#)) and ESG considerations ([Bolton and Kacperczyk 2021](#)) form alternative ways to consider affect (negatively or positively). Unfortunately, in unreported analyses, we only find neutral support for most of our implications using these approaches.²³ We desist from reporting these because of the modestly-sized cross-section of sin stocks, and the short time-series in which ESG considerations have been prevalent. Both these aspects reduce the power of asset pricing tests. It would be desirable to reconsider these dimensions as more data accumulates.

²³The basic evidence in [Hong and Kacperczyk \(2009\)](#) that sin stocks earn higher abnormal returns supports our setting (Proposition 3).

6 Conclusions

We address the joint impact of non-cashflow considerations and overconfidence on investors' demands, and in turn, on expected returns, within a multi-asset setting. Specifically, we consider the effects of a direct preference or affect for a firm's stock, direct consumption utility from trading (a gambling motive), and a form of overconfidence wherein investors underestimate the precision of public information they do not produce themselves. These motives for trade are supported by a survey we conduct on individual investors.

Our setting takes a first step towards integrating various behavioral elements within a common setting, as opposed to considering the elements in isolation. In our model, gambling amplifies volume that results from agreements to disagree on the model's parameters. Further, as overconfidence implies underreaction to public information, and gambling increases the extent of biased trading due to overconfidence, gambling effectively scales up the stock price underreaction to public information. Our analysis also suggests that in the cross-section of stocks, the risk-adjusted return decreases in the affect heuristic, and this relation is more pronounced when gambling propensity is high.

We also test the model's implications using data on U.S. equities, along with proxies for gambling propensity and affect investing. To measure the scale of the gambling propensity in a stock, we adopt the approach of [Kumar \(2009\)](#) and identify a stock as having a high level of gambling propensity (*GP*) if the stock has a low price, high idiosyncratic volatility, and high idiosyncratic skewness. Our findings support our theory: in the cross-section of stocks, turnover increases in *GP*; and the underreaction to earnings surprises ([Ball and Brown 1968](#); [Bernard and Thomas 1989](#)) and profit margins ([Novy-Marx 2013](#)) are more pronounced when *GP* is high. We follow [Grullon, Kanatas, and Weston \(2004\)](#) and [Lou \(2014\)](#) and use the growth of a firm's advertising spending in the product market as a metric for the strength of the affect heuristic. Again, our results are in line with our theory: in the cross-section of stocks, risk-adjusted return decreases in the growth of advertising spending; further, this negative relation becomes more pronounced when *GP* is high.

Our results underscore the value of considering attributes of investing that go beyond

traditional wealth maximization. In follow-up work, it may be useful to consider dynamic extensions of our setting where gambling propensities vary with asset moments such as volatility and skewness. The role of rational arbitrageurs in attenuating pricing effects caused by affect investing, gambling, and overconfidence also deserves a full investigation. These and other issues are left for future research.

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Appendix A

Proof of Theorem 1: (a) The i 'th OAG investor believes that

$$\begin{aligned} F|\tau &\sim N\left(\frac{\nu_F}{\hat{\nu}_\tau}\tau, \hat{\nu}_{F|\tau}\right), \text{ where } \hat{\nu}_{F|\tau} = \nu_F - \frac{\nu_F^2}{\hat{\nu}_\tau}; \text{ and} \\ \theta|s &\sim N\left(\nu_\theta \hat{\nu}_s^{-1}s, \hat{\nu}_{\theta|s}\right), \text{ where } \hat{\nu}_{\theta|s} = \nu_\theta - \nu_\theta^2 \hat{\nu}_s^{-1}. \end{aligned}$$

Write the investor's wealth at Date 1 as

$$W_{i1} = W_{i0}R_f + X_i'(V - PR_f) = W_{i0}R_f + X_i'(\bar{V} + \ell F + \theta + \xi - PR_f).$$

The investor perceives the wealth to be $W_{i1}^A = W_{i1} + X_i'A$, and derives non-wealth-related benefit $C_G(X_i) = 0.5X_i'GX_i$. The investor's demand X_i maximizes

$$\begin{aligned} U_{OAG}(W_{i1}^A, X_i) &= \hat{E}(W_{i1}^A|\tau, s) - 0.5\gamma \hat{\text{Var}}(W_{i1}^A|\tau, s) + C_G(X_i) \\ &= W_{i0}R_f + X_i' \left(A + \bar{V} + \ell \frac{\nu_F}{\hat{\nu}_\tau} \tau + \nu_\theta \hat{\nu}_s^{-1}s - PR_f \right) - 0.5\gamma X_i' \phi_{OAG} X_i, \end{aligned}$$

where $\phi_{OAG} = \ell \ell' \hat{\nu}_{F|\tau} + \hat{\nu}_{\theta|s} + \nu_\xi - G/\gamma$, and the second equality is based on the normality assumption. The first-order condition (f.o.c.) with respect to (w.r.t.) X_i implies that the optimal demand is:

$$X_{OAG} = \frac{\phi_{OAG}^{-1}}{\gamma} \left(A + \bar{V} + \ell \frac{\nu_F}{\hat{\nu}_\tau} \tau + \nu_\theta \hat{\nu}_s^{-1}s - PR_f \right). \quad (\text{A.1})$$

The second-order condition holds here and in other cases that follow, so we omit referencing it in the rest of the proofs.

(b) The i 'th rational investor has unbiased beliefs that

$$\begin{aligned} F|\tau &\sim N\left(\frac{\nu_F}{\nu_\tau}\tau, \nu_{F|\tau}\right), \text{ where } \nu_{F|\tau} = \nu_F - \frac{\nu_F^2}{\nu_\tau}; \text{ and} \\ \theta|s &\sim N\left(\nu_\theta \nu_s^{-1}s, \nu_{\theta|s}\right), \text{ where } \nu_{\theta|s} = \nu_\theta - \nu_\theta^2 \nu_s^{-1}. \end{aligned}$$

The investor's demand X_i maximizes:

$$\begin{aligned} U(W_{i1}) &= E(W_{i1}|\tau, s) - 0.5\gamma \text{Var}(W_{i1}|\tau, s) \\ &= W_{i0}R_f + X_i' \left(\bar{V} + \ell \frac{\nu_F}{\nu_\tau} \tau + \nu_\theta \nu_s^{-1}s - PR_f \right) - 0.5\gamma X_i' \phi X_i, \end{aligned}$$

where $\phi = \ell \ell' \nu_{F|\tau} + \nu_{\theta|s} + \nu_\xi$. The f.o.c. implies that the demand is expressed as:

$$X_{Rational} = \frac{\phi^{-1}}{\gamma} \left(\bar{V} + \ell \frac{\nu_F}{\nu_\tau} \tau + \nu_\theta \nu_s^{-1}s - PR_f \right). \quad (\text{A.2})$$

(c) From Equations (A.1) and (A.2), the market-clearing condition, $\eta X_{OAG} + (1-\eta)X_{Rational} = 1$, implies that the equilibrium prices P take the form as given in this theorem. $\square$

Proof of Proposition 1: Prior to proving this proposition, we first lay out the groundwork. This groundwork also serves as a foundation for proving Propositions 2 and 3.

Note that in the simple economy, the variance of the firm-specific payoff $\theta_j + \xi_j$ (denoted by ν) is identical across stocks and the information signal about θ_j , denoted by s_j , is not informative. See Equation (2). According to the formula in Sherman and Morrison (1950),²⁴ we have:

$$\begin{aligned}\phi_{OAG}^{-1} &= \frac{1}{\nu} \left[(\mathbf{I} - G^*)^{-1} - \frac{(\mathbf{I} - G^*)^{-1} \ell \ell' (\mathbf{I} - G^*)^{-1}}{\hat{\nu}_{F|\tau}^{-1} \nu + \ell' (\mathbf{I} - G^*)^{-1} \ell} \right], \\ \phi^{-1} &= \frac{1}{\nu} \left(\mathbf{I} - \frac{\ell \ell'}{\nu_{F|\tau}^{-1} \nu + \ell' \ell} \right),\end{aligned}\tag{A.3}$$

where $G^* = G/(\gamma\nu)$, and $\mathbf{I}$ is a $J \times J$ identity matrix. We can express $\Phi = \nu^{-1} (\Phi_1 + \Phi_0)$, where

$$\Phi_1 = \eta (\mathbf{I} - G^*)^{-1} + (1 - \eta) \mathbf{I},\tag{A.4}$$

$$\Phi_0 = - \left[\eta \frac{(\mathbf{I} - G^*)^{-1} \ell \ell' (\mathbf{I} - G^*)^{-1}}{\hat{\nu}_{F|\tau}^{-1} \nu + \ell' (\mathbf{I} - G^*)^{-1} \ell} + (1 - \eta) \frac{\ell \ell'}{\nu_{F|\tau}^{-1} \nu + \ell' \ell} \right].\tag{A.5}$$

From the matrix identity in Woodbury (1950),²⁵ we have

$$\Phi^{-1} = \nu \left[\Phi_1^{-1} - \Phi_1^{-1} \Phi_0 (\mathbf{I} + \Phi_1^{-1} \Phi_0)^{-1} \Phi_1^{-1} \right].\tag{A.6}$$

Suppose that in the simple economy, the conditional factor payoff is significantly less volatile than the conditional firm-specific payoff. For notational convenience, let $\nu_F^{-1} \nu \rightarrow \infty$; this implies $\nu_{F|\tau}^{-1} \nu \rightarrow \infty$ and $\hat{\nu}_{F|\tau}^{-1} \nu \rightarrow \infty$. We can use Equations (A.5) and (A.6) to show that

$$\Phi_0 \rightarrow \mathbf{0}_{J \times J} \text{ and } \Phi^{-1} \rightarrow \nu \Phi_1^{-1}.\tag{A.7}$$

Equation (A.4) implies that Φ_1 is a diagonal matrix: It is straightforward to show that

²⁴Specifically, let M be a $J \times J$ matrix and Λ be a $J \times 1$ vector. Suppose that M is invertible and that $1 + \Lambda' M^{-1} \Lambda \neq 0$. Then, $(M + \Lambda \Lambda')^{-1} = M^{-1} - \frac{M^{-1} \Lambda \Lambda' M^{-1}}{1 + \Lambda' M^{-1} \Lambda}$.

²⁵Specifically, let M and N be two $J \times J$ matrices. Assume that M is invertible and that $\mathbf{I} + M^{-1} N$ is also invertible. Then, $(M + N)^{-1} = M^{-1} - M^{-1} N (\mathbf{I} + M^{-1} N)^{-1} M^{-1}$.

- $d(\Phi_1^{-1})/d\rho = \mathbf{0}_{J \times J}$;
- $d(\Phi_1^{-1})/dG_j \propto -\mathbf{I}_{jj}$, where $\mathbf{I}_{jj}$ is a $J \times J$ matrix where the j 'th diagonal element equals 1 and other elements equals 0.

Since $\nu_{F|\tau}^{-1}\nu \rightarrow \infty$ and also $\hat{\nu}_{F|\tau}^{-1}\nu \rightarrow \infty$, it follows from Equation (A.5) that

- $d\Phi_0/d\rho \rightarrow \mathbf{0}_{J \times J}$;
- $d\Phi_0/dG_j \rightarrow \mathbf{0}_{J \times J}$.

See the expression of Φ^{-1} in Equation (A.6). Note from the previous derivation that $\Phi_0 \rightarrow \mathbf{0}_{J \times J}$, $d\Phi_0/d\rho \rightarrow \mathbf{0}_{J \times J}$, and $d(\Phi_1^{-1})/d\rho \rightarrow \mathbf{0}_{J \times J}$; it follows that

$$\frac{d(\Phi^{-1})}{d\rho} \rightarrow \mathbf{0}_{J \times J}. \quad (\text{A.8})$$

Note from the previous derivation that $\Phi_0 \rightarrow \mathbf{0}_{J \times J}$, $d\Phi_0/dG_j \rightarrow \mathbf{0}_{J \times J}$, and $d(\Phi_1^{-1})/dG_j \propto -\mathbf{I}_{jj}$; it follows that

$$\frac{d(\Phi^{-1})}{dG_j} \rightarrow \nu \frac{d(\Phi_1^{-1})}{dG_j} \propto -\mathbf{I}_{jj}. \quad (\text{A.9})$$

This completes the preparation for the subsequent analysis.

Now we prove Proposition 1 using Theorem 2. We substitute the equilibrium price into the demands of each investor type, which yields

$$\begin{aligned} X_{OAG} &= \frac{\phi_{OAG}^{-1}}{\gamma} [(\mathbf{I} - \Phi^{-1}\eta\phi_{OAG}^{-1})(A + \ell\Delta\tau) + \Phi^{-1}\gamma\mathbf{1}], \\ X_{Rational} &= -\frac{\phi^{-1}}{\gamma} \Phi^{-1} [\eta\phi_{OAG}^{-1}(A + \ell\Delta\tau) - \gamma\mathbf{1}]. \end{aligned}$$

Note that the demand for the j 'th stock by each of the two investor types, denoted as $X_{OAG,j}$ and $X_{Rational,j}$, is simply the j 'th element of the vectors X_{OAG} and $X_{Rational}$, respectively.

$$X_{OAG,j} - E(X_{OAG,j}) = \psi_{OAG,j}\Delta\tau \quad \text{and} \quad X_{Rational,j} - E(X_{Rational,j}) = \psi_j\Delta\tau, \quad (\text{A.10})$$

where

$$\psi_{OAG,j} = \frac{1}{\gamma} \mathbf{1}'_j \phi_{OAG}^{-1} (\mathbf{I} - \Phi^{-1}\eta\phi_{OAG}^{-1}) \ell \quad \text{and} \quad \psi_j = -\frac{1}{\gamma} \mathbf{1}'_j \phi^{-1} \Phi^{-1} \eta \phi_{OAG}^{-1} \ell. \quad (\text{A.11})$$

It is straightforward to verify that $\eta\psi_{OAG,j} + (1 - \eta)\psi_j = 0$.

If $\rho = 1$, then it follows from Equation (1) that $\Delta = 0$. We can use Equations (4) and (A.10) to show that $E(T_j^*) = 0$. This proves Part (i) of this proposition.

If $\rho > 1$, suppose that $\ell_j > 0$ (we can modify the derivation here to show that the results also apply to the case with $\ell_j < 0$). Then, from Equation (A.11), we have

$$\begin{aligned}
\psi_{OAG,j} &= \frac{1}{\gamma\nu} \mathbf{1}'_j \left[(\mathbf{I} - G^*)^{-1} - \frac{(\mathbf{I} - G^*)^{-1} \ell \ell' (\mathbf{I} - G^*)^{-1}}{\hat{\nu}_{F|\tau}^{-1} \nu + \ell' (\mathbf{I} - G^*)^{-1} \ell} \right] \\
&\quad \left[\mathbf{I} - \Phi^{-1} \frac{\eta}{\nu} \left[(\mathbf{I} - G^*)^{-1} - \frac{(\mathbf{I} - G^*)^{-1} \ell \ell' (\mathbf{I} - G^*)^{-1}}{\hat{\nu}_{F|\tau}^{-1} \nu + \ell' (\mathbf{I} - G^*)^{-1} \ell} \right] \right] \ell \quad (\text{A.12}) \\
&\rightarrow \frac{1}{\gamma\nu} \mathbf{1}'_j (\mathbf{I} - G^*)^{-1} [\mathbf{I} - \Phi_1^{-1} \eta (\mathbf{I} - G^*)^{-1}] \ell \\
&\propto \frac{1 - \eta}{\eta + (1 - \eta)(1 - G_j/(\gamma\nu))} \ell_j \\
&> 0
\end{aligned}$$

where the equality follows from the expression of ϕ_{OAG} in Equation (A.3), the $\rightarrow$ follows from Equation (A.7) and the fact that $\hat{\nu}_{F|\tau}^{-1} \nu \rightarrow \infty$ in the simple economy, and the inequality follows from the assumption that $\ell_j > 0$. It follows from the previously derived $\eta\psi_{OAG,j} + (1 - \eta)\psi_j = 0$ that $\psi_j < 0$.

See the expression of $\psi_{OAG,j}$ in Equation (A.12). It follows from the fact $\hat{\nu}_{F|\tau}^{-1} \nu \rightarrow \infty$ and the previously derived $d(\Phi^{-1})/d\rho \rightarrow \mathbf{0}_{J \times J}$ (see Equation (A.8)) that

$$\frac{d\psi_{OAG,j}}{d\rho} \rightarrow 0.$$

See the expression of Φ^{-1} in Equation (A.6) depending on Φ_1 and Φ_0 given in Equations (A.4) and (A.5). Note that $\hat{\nu}_{F|\tau}^{-1} \nu$ and $\nu_{F|\tau}^{-1} \nu \rightarrow \infty$. We can use Equation (A.12) to show that

$$\begin{aligned}
\frac{d\psi_{OAG,j}}{dG_j} &\rightarrow \frac{d}{dG_j} \left[\frac{1}{\gamma\nu} \mathbf{1}'_j (\mathbf{I} - G^*)^{-1} [\mathbf{I} - \Phi_1^{-1} \eta (\mathbf{I} - G^*)^{-1}] \ell \right] \\
&\propto \frac{d}{dG_j} \left[\frac{1 - \eta}{\eta + (1 - \eta)(1 - G_j/(\gamma\nu))} \ell_j \right] \\
&> 0.
\end{aligned}$$

Consider Equations (4) and (A.10). Using the previously derived results that $\psi_{OAG,j} > 0$, $\psi_j < 0$, and $\eta\psi_{OAG,j} + (1 - \eta)\psi_j = 0$, we obtain

$$E(T_j^*) = 0.5\eta\psi_{OAG,j}E(|\Delta\tau|) - 0.5(1 - \eta)\psi_jE(|\Delta\tau|) = \eta\psi_{OAG,j}E(|\Delta\tau|). \quad (\text{A.13})$$

Note from the previous derivation that $d\psi_{OAG,j}/d\rho \rightarrow 0$; it follows that

$$\frac{dE(T_j^*)}{d\rho} \rightarrow \eta\psi_{OAG,j} \frac{dE(|\Delta\tau|)}{d\rho} \propto \frac{d|\Delta|}{d\rho} > 0,$$

where the last inequality obtains from the expression of Δ in Equation (1). From the earlier derivation, we also have $d\psi_{OAG,j}/dG_j > 0$ given that $\ell_j > 0$; it follows that

$$\frac{dE(T_j^*)}{dG_j} \propto \frac{d\psi_{OAG,j}}{dG_j} > 0.$$

This proves Part (ii) of this proposition. $\square$

Proof of Proposition 2: Note that in the simple economy, the firm-specific signal s_j is not informative. Using Equations (5) and (6), we can compute

$$\text{Cov}(r_j, S_j) = -(1 - \mu)\mathbf{1}_j' \Phi^{-1} \eta \phi_{OAG}^{-1} \ell \Delta \nu_\tau. \quad (\text{A.14})$$

If $\rho = 1$, then it follows from Equation (2) that $\Delta = 0$; in this case, $\text{Cov}(r_j, S_j) = 0$.

Suppose $\rho > 1$. Then, $\hat{\nu}_\tau > \nu_\tau$; it follows from Equation (1) that $\Delta < 0$. In this case,

$$\begin{aligned} \text{Cov}(r_j, S_j) &\propto \mathbf{1}_j' \Phi^{-1} \eta \phi_{OAG}^{-1} \ell \\ &\rightarrow \mathbf{1}_j' \Phi_1^{-1} \eta \left[(\mathbf{I} - G^*)^{-1} - \frac{(\mathbf{I} - G^*)^{-1} \ell \ell' (\mathbf{I} - G^*)^{-1}}{\hat{\nu}_{F|\tau}^{-1} \nu + \ell' (\mathbf{I} - G^*)^{-1} \ell} \right] \ell \\ &\rightarrow \mathbf{1}_j' \Phi_1^{-1} \eta (\mathbf{I} - G^*)^{-1} \ell \\ &= \frac{\eta}{\eta + (1 - \eta)(1 - G_j/(\gamma\nu))} \ell_j, \end{aligned} \quad (\text{A.15})$$

where the first $\rightarrow$ follows from Equation (A.7) and the expression for ϕ_{OAG}^{-1} in Equation (A.3), and the second $\rightarrow$ follows from the fact that $\hat{\nu}_{F|\tau}^{-1} \nu \rightarrow \infty$ in the simple economy. Therefore, given $\ell_j > 0$, $\text{Cov}(r_j, S_j) > 0$.

See the expression of $\text{Cov}(r_j, S_j)$ in Equation (A.14). Note from Equations (A.3) and (A.6) that

$$\frac{d(\Phi^{-1} \phi_{OAG}^{-1})}{dG_j} \rightarrow \frac{d(\Phi_1^{-1} (\mathbf{I} - G^*)^{-1})}{dG_j} \propto \mathbf{I}_{jj},$$

where the $\rightarrow$ obtains from $\hat{\nu}_{F|\tau}^{-1} \nu \rightarrow \infty$ and the previously derived $\Phi_0, d\Phi_0/dG_j \rightarrow 0_{J \times J}$.

For $d\text{Cov}(r_j, S_j)/dG_j > 0$, it suffices to show that

$$\begin{aligned}
\frac{d}{dG_j} \left(\frac{\mathbf{1}'_j \Phi^{-1} \eta \phi_{OAG}^{-1} \ell \Delta^2 \nu_\tau}{\ell_j} \right) &\propto \frac{1}{\ell_j} \mathbf{1}'_j \frac{d(\Phi^{-1} \phi_{OAG}^{-1})}{dG_j} \ell \\
&\rightarrow \frac{1}{\ell_j} \mathbf{1}'_j \frac{d(\Phi_1^{-1} (\mathbf{I} - G^*)^{-1})}{dG_j} \ell \\
&\propto \frac{1}{\ell_j} \mathbf{1}'_j \mathbf{I}_{jj} \ell = 1 > 0.
\end{aligned} \tag{A.16}$$

□

Proof of Proposition 3: Suppose that $\rho = 1$ and $\forall j \ A_j = G_j = 0$. It follows from Equation (2) that $\Delta = 0$ and $\Phi = \phi^{-1}$. Using Theorem 2, we can express the excess return vector as

$$r = V - PR_f = \ell \left(F - \frac{\nu_F}{\nu_\tau} \tau \right) + \theta + \xi + \gamma \phi \mathbf{1}.$$

Note that by definition, $r_M = \mathbf{1}'r/J$. It follows that

$$\begin{aligned}
E(r) &= \gamma \phi \mathbf{1}, \quad E(r_M) = \gamma \mathbf{1}' \phi \mathbf{1} / J, \\
\text{Var}(r) &= \phi, \quad \text{Cov}(r, r_M) = \phi \mathbf{1} / J, \quad \text{and} \quad \text{Var}(r_M) = \mathbf{1}' \phi \mathbf{1} / J^2.
\end{aligned}$$

We can express the risk-adjusted expected return vector as:

$$\alpha = E(r) - \beta_m E(r_M) = \gamma \phi \mathbf{1} - \frac{\phi \mathbf{1} / J}{\mathbf{1}' \phi \mathbf{1} / J^2} \gamma \mathbf{1}' \phi \mathbf{1} / J = \mathbf{0}_{J \times 1};$$

it follows that $\alpha_j = \mathbf{1}'_j \alpha = 0$. This proves Part (i) of this proposition.

Now suppose that $\rho > 1$ and $\exists j$ such that $A_j \neq 0$ and/or $G_j > 0$. It is straightforward to compute β_{jM} and show that it does not depend on A_j .

Note from Equations (8) and (9) that

$$\alpha_j = E(r_j) - \beta_{jM} E(r_M), \text{ where } E(r_j) = \mathbf{1}'_j \Phi^{-1} (\gamma \mathbf{1} - \eta \phi_{OAG}^{-1} A).$$

Observe that $E(r_M)$ is identical across all stocks and that β_{jM} does not depend on A_j , as proved above. For Part (ii) of this proposition, it suffices to show that

$$\frac{\partial E(r_j)}{\partial A_j} = -\mathbf{1}'_j \Phi^{-1} \eta \phi_{OAG}^{-1} \mathbf{1}_j \rightarrow -\frac{\eta}{\eta + (1 - \eta)(1 - G_j/(\gamma \nu))} < 0,$$

where we use a similar derivation as in the proof of Proposition 2 (see Equation A.15) to obtain the $\rightarrow$. Further, we can use a similar derivation as in the proof of Proposition 2 (see Equation A.16) to obtain

$$\frac{\partial}{\partial G_j} \left(\frac{\partial E(r_j)}{\partial A_j} \right) \propto -\mathbf{1}'_j \frac{d(\Phi^{-1} \phi_{OAG}^{-1})}{dG_j} \mathbf{1}_j \propto -1 < 0.$$

□

Appendix B

This table describes how we compute the variables used in our empirical analysis.

Variables	Definition
<i>TO</i>	For each stock-month, <i>TO</i> is the turnover computed as monthly shares traded as reported by CRSP, scaled by the number of outstanding shares at the end of the past month. To address double counting in NASDAQ turnover, due to the recording of inter-dealer trades, we follow Gao and Ritter (2010) to divide the turnover of NASDAQ stocks by 2.0 before January 2001, by 1.8 for the rest of 2001, by 1.6 for 2002-2003, and leave it unchanged thereafter.
<i>Risk-adjusted return</i>	For each stock-month, we use the stock's excess return over the risk-free interest rate or the difference between the stock return and the benchmark-implied return in the month. We estimate benchmark models, including the CAPM, the Fama and French (1993) and Carhart (1997) 4-factor model (FFC4), and the Fama and French (2015) 5-factor model (FF5), using at least 18 monthly returns in the past 36 months.
<i>SUE</i>	For each stock-month, we compute the standardized unexpected earnings (<i>SUE</i>) using the quarterly report released in the past three months. For stock-quarter q , we follow Foster, Olsen, and Shevlin (1984) to estimate for the stock (j)'s earnings per share (<i>EPS</i>) the regression $EPS_{j,q} = a + b EPS_{j,q-4} + \epsilon_{j,q}$ using at least 10 observations in the past 20 quarters. <i>SUE</i> is the difference between the actual <i>EPS</i> and the expected <i>EPS</i> based on the <i>EPS</i> in quarter $q - 4$, scaled by $SD(\epsilon_{j,q})$ from the regression.
<i>Profitability</i>	For each stock-month, we use the quarterly report announced in the past three months to compute <i>Profitability</i> as the ratio of a firm's gross profits (revenues minus cost of goods sold) in the quarter to its assets at the beginning of the quarter.
<i>PRC</i>	For each stock-month, <i>PRC</i> is computed as the average stock price using at least 90 daily data in the past 6 months.
<i>IVOL</i>	For each stock-month, <i>IVOL</i> is the idiosyncratic volatility computed as the standard deviation of the residuals from the Fama and French (2015) five-factor model using at least 90 daily data in the past 6 months.
<i>ISKEW</i>	For each stock-month, <i>ISKEW</i> is the idiosyncratic skewness computed as the skewness of the residuals from the Fama and French (2015) five-factor model using at least 90 daily data in the past 6 months.
<i>GP</i>	For each stock-month, the gambling propensity $GP = 1$ if in the cross-section, the <i>PRC</i> is in the bottom three deciles, the <i>IVOL</i> is in the top three deciles, and the <i>ISKEW</i> is in the top three deciles; otherwise, $GP = 0$.

<i>ADV</i>	For each stock-month from July of a year to June of the next year, we use the annual report in the past fiscal year to compute <i>ADV</i> , the growth of the advertising expense (<i>XAD</i>). For a fiscal year <i>y</i> , we compute for the stock <i>j</i> : $ADV_{j,y} = \ln(XAD_{j,y} + 1) - \ln(XAD_{j,y-1} + 1)$; we further de-mean this <i>ADV</i> by the cross-sectional industrial average <i>ADV</i> , and scaled the result by the cross-sectional standard deviation of the <i>ADV</i> in the industry.
<i>ME</i>	For each stock-month, we use the stock's market value of equity (i.e., the stock price $\times$ the number of outstanding shares) as of the end of the past month.
<i>Firm age</i>	For each stock-month, we use the number of months since the stock's first CRSP appearance as of the end of the past month.
<i>BM</i>	For each stock-month from July of a year to June of the next year, we compute the book-to-market ratio using the book equity as of the end of the past fiscal year, and the market value of equity as of the end of the past calendar year. We follow Fama and French (1993) and require both the market equity and the book equity to be positive.
<i>D/A</i>	For each stock-month from July of a year to June of the next year, we use the stock's book debt (i.e., the sum of short-term and long-term debt) divided by total assets as of the end of the past fiscal year.
<i>EVOLA</i>	For each stock-month, we compute the earnings volatility of the stock as the standard deviation of <i>EPS</i> using at least 10 quarters in the past 20 quarters.
<i>ANA</i>	For each stock-month, we use the number of analysts who follow the firm and report forecasts to the I/B/E/S database in the past month.
<i>FDISP</i>	For each stock-month, we use the stock's analyst forecast dispersion, which is computed as the standard deviation of <i>EPS</i> forecasts reported by analysts in the I/B/E/S database in the past month.
<i>AT</i>	For each stock-month, we compute the turnover-based Amihud (2002) illiquidity measure as the average of the ratio of the daily absolute return to daily turnover using at least 90 daily data in the past six months.

Figure 1: Expected turnover as a function of gambling propensity, for different levels of overconfidence

This graph plots the expected turnover $E(T_j)$ for each stock as a function of gambling propensity G_j , for different levels of the overconfidence bias (ρ). We consider an economy with $J = 200$ stocks, where the G_j values are evenly distributed on the support $[0, 0.5]$, and the A_j values are evenly distributed on the support $[-2, 2]$. The other parameter values are $\gamma = 2$ and $\eta = 0.5$; $\forall j \ell_j = 1$, $\nu_{\theta_j} = 1$, $\nu_{\epsilon_j} = \nu_{\theta_j}/2$, and $\nu_{\xi_j} = 0.01$; $\nu_F = 0.01$ and $\nu_\zeta = \nu_F/2$. We assume that each type of investors' endowments equal the ex ante means of their optimal demands (i.e., $\forall j Y_{OAG,j} = E(X_{OAG,j})$ and $Y_{Rational,j} = E(X_{Rational,j})$).

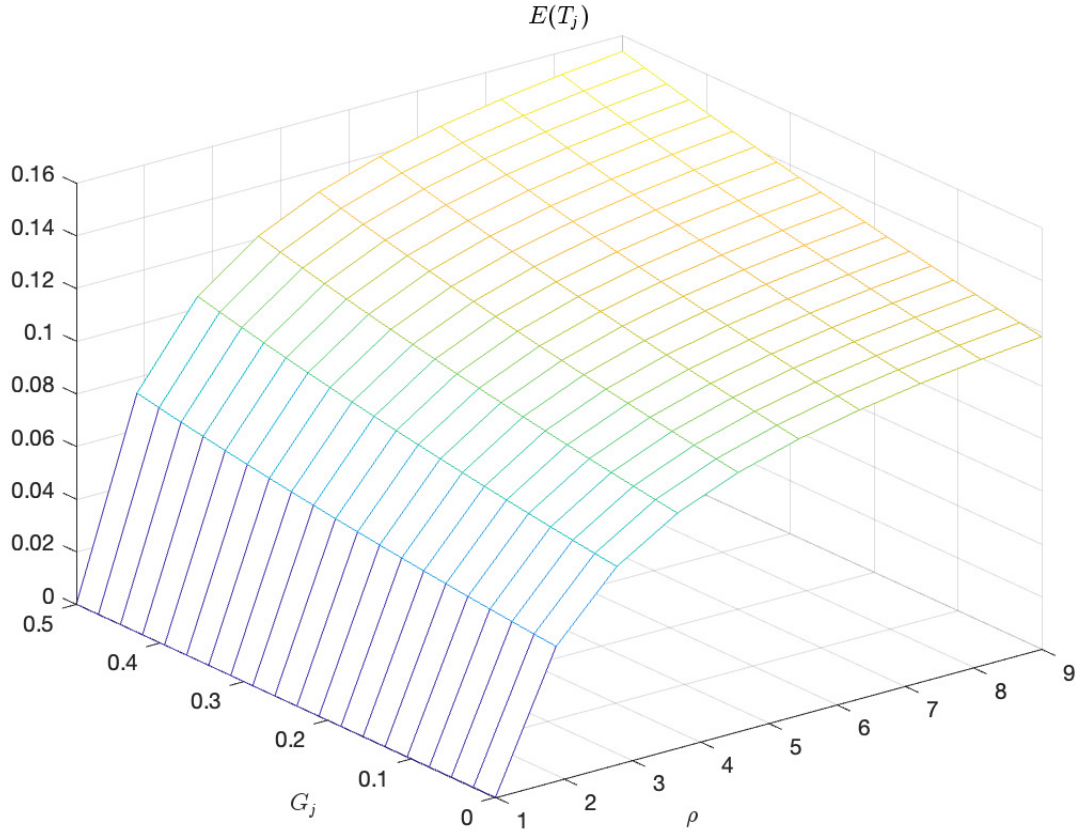


Figure 2: Expected turnover, gambling propensity, and the affect heuristic

This graph plots the expected turnover $E(T_j)$ for each stock as a function of the gambling propensity G_j and the affect parameter A_j . We consider an economy with $J = 200$ stocks, where the G_j values are evenly distributed on the support $[0, 0.5]$, and the A_j values are evenly distributed on the support $[-2, 2]$. The other parameter values are $\gamma = 2$ and $\eta = 0.5$; $\forall j \ell_j = 1$, $\nu_{\theta_j} = 1$, $\nu_{\epsilon_j} = \nu_{\theta_j}/2$, and $\nu_{\xi_j} = 0.01$; $\nu_F = 0.01$ and $\nu_\zeta = \nu_F/2$; and $\rho = 9$. We assume that each type of investor's endowments equal per capita supplies (i.e., $\forall j Y_{OAG,j} = Y_{Rational,j} = 1$) in Panel A, and that all endowments equal zero (i.e., $\forall j Y_{OAG,j} = Y_{Rational,j} = 0$) in Panel B.

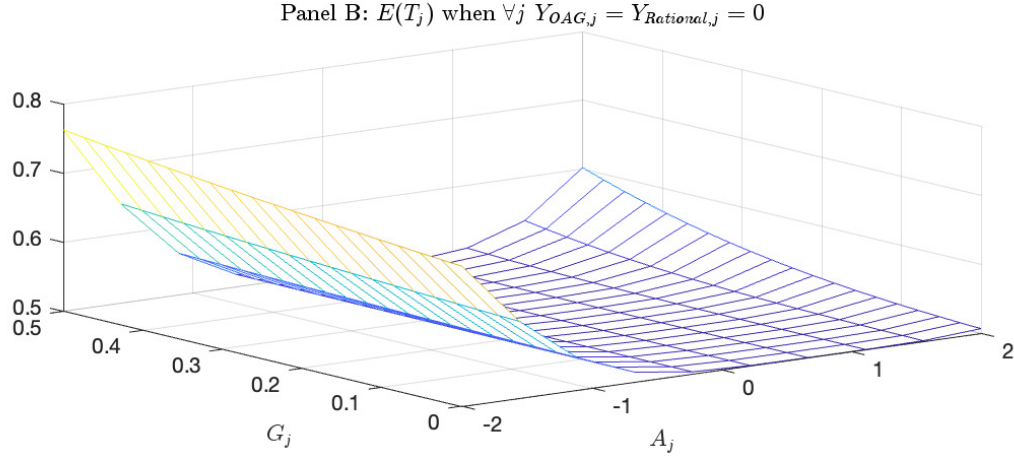
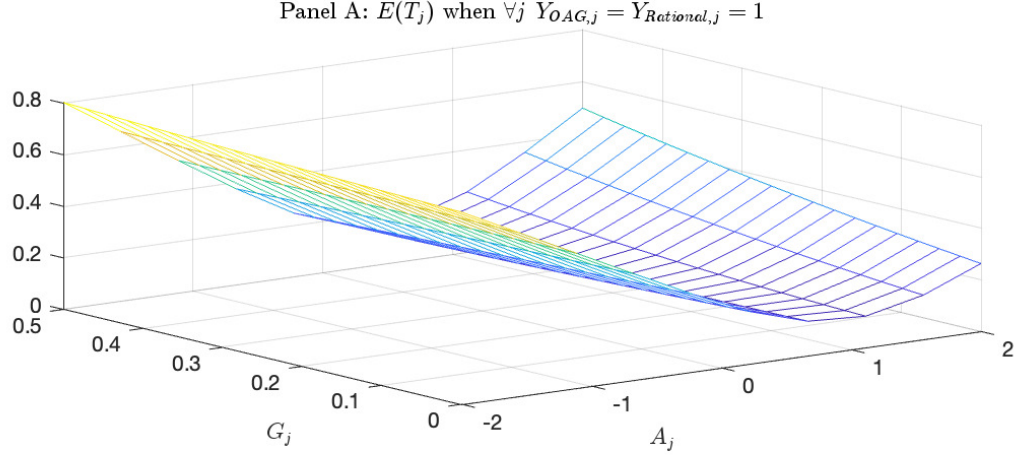


Figure 3: Level of underreaction to public information as a function of gambling propensity

This graph plots the post-public-announcement drift (as measured by $\text{Cov}(r_j, S_j)$) for each stock as a function of the gambling propensity G_j , for different levels of the overconfidence bias (ρ). We consider an economy with $J = 200$ stocks, where the G_j values are evenly distributed on the support $[0, 0.5]$, and the A_j values are evenly distributed on the support $[-2, 2]$. The other parameter values are $\gamma = 2$ and $\eta = 0.5$; $\forall j \ell_j = 1$, $\nu_{\theta_j} = 1$, $\nu_{\epsilon_j} = \nu_{\theta_j}/2$, and $\nu_{\xi_j} = 0.01$; $\nu_F = 0.01$ and $\nu_\zeta = \nu_F/2$; and $\mu = 0.8$.

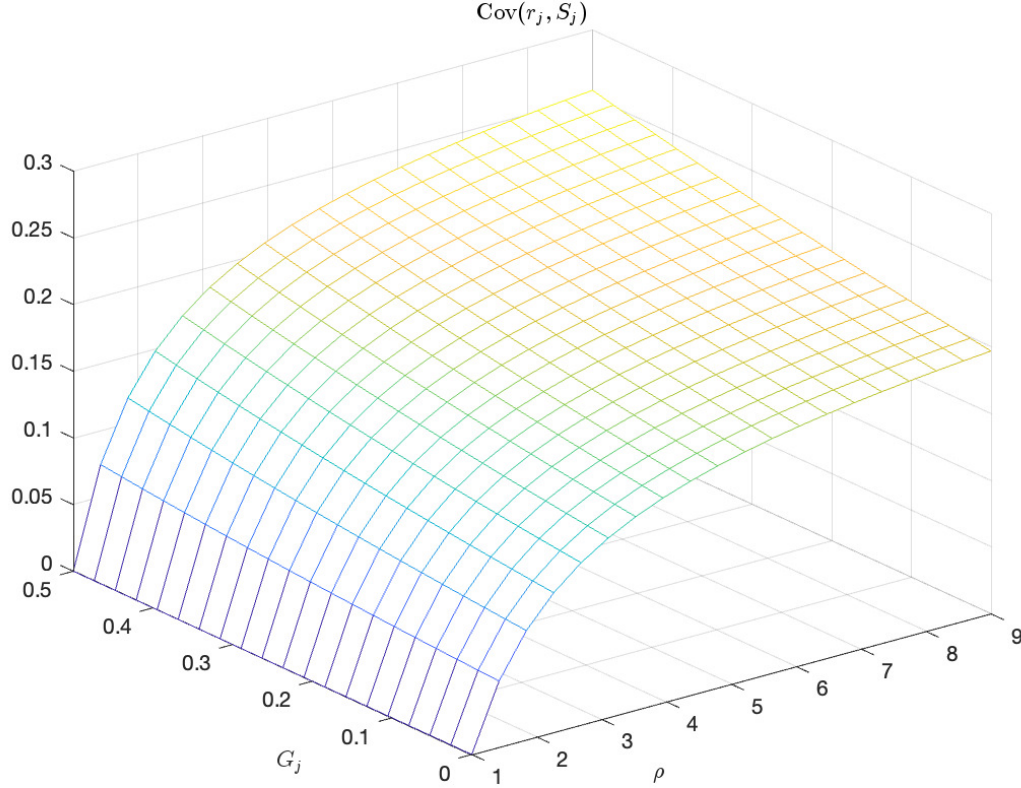


Figure 4: Risk-adjusted expected returns, gambling propensity, and the affect heuristic
This graph plots the risk-adjusted expected return α_j for each stock as a function of the gambling propensity G_j and the affect parameter A_j . We consider an economy with $J = 200$ stocks, where the G_j values are evenly distributed on the support $[0, 0.5]$, and the A_j values are evenly distributed on the support $[-2, 2]$. The other parameter values are $\gamma = 2$ and $\eta = 0.5$; $\forall j \ell_j = 1$, $\nu_{\theta_j} = 1$, $\nu_{\epsilon_j} = \nu_{\theta_j}/2$, and $\nu_{\xi_j} = 0.01$; $\nu_F = 0.01$ and $\nu_\zeta = \nu_F/2$; and $\rho = 9$.

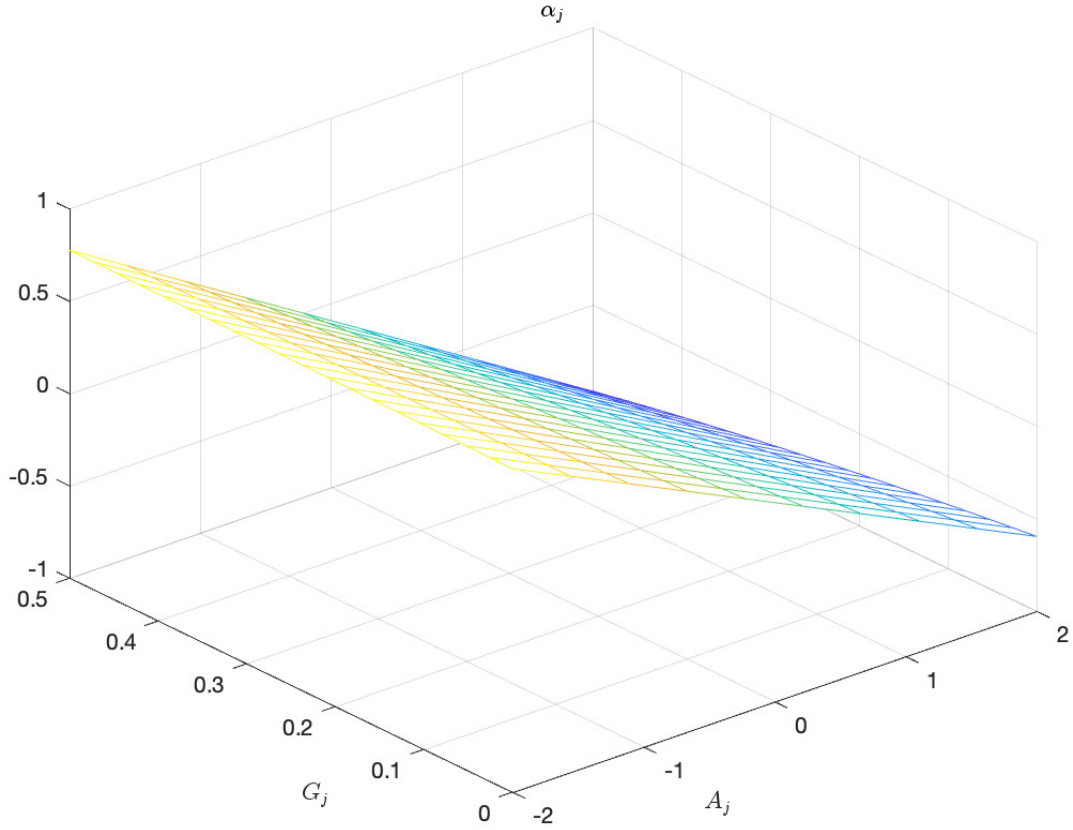


Table 1: Summary statistics of the survey participants

This table presents summary statistics for the sample of 481 U.S. retail investors who participate in the survey. Panel A reports investor characteristics. Panel B reports household-level financial information. Panel C reports the correct response rates for the two financial literacy questions. “NA” indicates “Prefer not to answer.”

Panel A: Investor characteristics

Gender		Age		Education		Investment age	
Male	64.78%	< 30	13.42%	Secondary school / High school	9.77%	< 1 year	1.66%
Female	35.22%	30 to 40	32.29%	Diploma / Technical or vocational training	10.4%	1 to 3 years	14.35%
		40 to 50	22.43%	Bachelor’s degree	51.77%	4 to 6 years	21.21%
		50 to 60	19.71%	Master’s degree	22.25%	7 to 10 years	18.3%
		> 60	12.16%	Doctoral degree	5.2%	> 10 years	44.07%
				Others	0.21%	NA	0.42%
				NA	0.42%		

Panel B: Household-level financial information

Annual income		Net worth		Stock investment	
< \$20,000	1.25%	< \$50,000	11.64%	< \$10,000	15.59%
\$20,000 to \$39,999	7.48%	\$50,000 to \$99,999	13.31%	\$10,000 to \$49,999	22.25%
\$40,000 to \$59,999	10.19%	\$100,000 to \$249,999	19.54%	\$50,000 to \$99,999	16.63%
\$60,000 to \$79,999	17.05%	\$250,000 to \$499,999	15.18%	\$100,000 to \$249,999	15.18%
\$80,000 to \$99,999	16.42%	\$500,000 to \$999,999	16.84%	\$250,000 to \$499,999	11.23%
\$100,000 to \$149,999	24.12%	\$1,000,000 to \$1,999,999	10.81%	\$500,000 to \$999,999	6.03%
\$150,000 to \$199,999	12.89%	> \$2,000,000	7.48%	> \$1,000,000	8.11%
> \$200,000	8.11%	NA	5.2%	NA	4.99%
NA	2.49%				

Panel C: Financial literacy

Question	Correct rate
1. When an investor buys and holds shares of a company, what do they own?	91.48%
2. When you hold a company’s stock, what kind of payoff might you receive?	95.84%

Table 2: Distribution of responses to survey questions

This table presents the distribution of responses from U.S. retail investors to survey questions on rational trading (Panel A), overconfidence (Panel B), the affect heuristic (Panel C), and gambling propensity (Panel D). “NA” indicates “Don’t know” or “Prefer not to answer.” For each question, responses are scored on a 1–5 scale (1 = most negative; 5 = most positive). We report the mean and median scores, the percentage of responses scored 4 or 5, and the difference between this percentage and that of responses scored 1 or 2. *, ** and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Score=1	2	3	4	Score=5	Mean	Median	Score=4/5	4/5 vs. 1/2
Panel A: Rational trading									
R1. How likely are you to trade stocks based on a fundamental analysis of a firm (e.g., using past financials or a cash flow model)?	Very unlikely 4.4%	Unlikely 6.4%	Neutral 11.6%	Likely 55.9%	Very likely 19.8%	NA 1.9%	3.8	4	75.7% 64.9%***
R2. How likely are you to trade stocks because to you need rebalance or diversify your portfolio?	Very unlikely 3.3%	Unlikely 10.2%	Neutral 20.6%	Likely 51.6%	Very likely 13.3%	NA 1%	3.6	4	64.9% 51.4%***
R3. Do you agree with the following statement? One of the reasons I buy certain stocks is because I receive positive information about them from public sources (e.g., earnings announcements).	Strongly disagree 3.7%	Disagree 7.30%	Neutral 12.9%	Agree 65.9%	Strongly agree 8.30%	NA 1.9%	3.7	4	74.2% 63.2%***

Table 2 continued.

	Score=1	2	3	4	Score=5	Mean	Median	Score=4/5	4/5 vs. 1/2
Panel B: Overconfidence									
O1. When you make investments in the stock market. How likely do you believe your investment returns will be above the market average over the next 12 months?	Very unlikely 2.1%	Unlikely 12.9%	Neutral 32%	Likely 44.9%	Very likely 6.7%	NA 1.5%	3.4	4	51.6% 36.6%***
O2. How would you rate your ability to pick winning stocks?	Much worse than average 1.9%	Slightly worse 9.80%	About average 58.2%	Slightly better 22.2%	Much better than average 3.7%	NA 4.2%	3.2	3	26% 14.3%***
Panel C: Affect heuristics									
A1. Do you agree with the following statement? When I trade stocks, my decisions are influenced by my perceptions of and familiarity with the company's products.	Strongly disagree 2.7%	Disagree 11%	Neutral 14.6%	Agree 57.2%	Strongly agree 13.1%	NA 1.5%	3.7	4	70.3% 56.5%***
A2. Do you agree with the following statement? When I trade stocks, I tend to invest in companies that share my values and principles.	Strongly disagree 4.80%	Disagree 15.6%	Neutral 31.6%	Agree 37.6%	Strongly agree 8.30%	NA 2.1%	3.3	3	45.9% 25.6%***

Table 2 continued.

	Score=1	2	3	4	Score=5	Mean	Median	Score=4/5	4/5 vs. 1/2
Panel D: Gambling									
G1. Do you agree with the following statement? When trading stocks, I tend to view them like lotteries; I am comfortable accepting small losses if they offer the chance of a big gain.	Strongly disagree 7.7%	Disagree 20.4%	Neutral 15%	Agree 49.5%	Strongly agree 6.9%	NA 0.6%	3.3	4	56.3% 28.3%***
G2. Do you agree with the following statement? When I trade stocks, I enjoy the excitement and thrill.	Strongly disagree 8.70%	Disagree 18.7%	Neutral 24.1%	Agree 38.7%	Strongly agree 8.9%	NA 0.8%	3.2	3	47.6% 20.2%***

Table 3: Pairwise correlation coefficients of scores based on survey responses

For each survey question listed in Table 2 on rational trading (R1-R3), overconfidence (O1-O2), an affect heuristic (A1-A2), and gambling propensity (G1-G2), responses are scored on a 1–5 scale (1 = most negative; 5 = most positive). This table reports the pair-wise correlation coefficients among those scores. *, ** and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) R1 (fundamental analysis)	1								
(2) R2 (rebalancing/diversification)	0.102**	1							
(3) R3 (information)	0.340***	0.052	1						
(4) O1 (beating the market)	0.212***	0.095**	0.205***	1					
(5) O2 (picking winning stocks)	0.189***	0.145***	0.085*	0.390***	1				
(6) A1 (product perceptions/familiarity)	0.225***	0.075*	0.241***	0.212***	0.079*	1			
(7) A2 (company values/principles)	0.192***	0.158***	0.167***	0.166***	0.121***	0.387***	1		
(8) G1 (lotteries)	0.049	0.026	0.096**	0.226***	0.096**	0.184***	0.079*	1	
(9) G2 (excitement/thrill)	0.169***	0.150***	0.199***	0.333***	0.313***	0.265***	0.186***	0.352***	1

Table 4: Summary statistics

For each stock-month, TO is the turnover computed as the monthly shares traded, scaled by the number of outstanding shares at the end of the past month. $r_{j,t}$ is the return of the stock (j) in the month (t). We use the quarterly report released in the past three months to compute the standardized unexpected earnings (SUE) and gross margins ($Profitability$). We use at least 90 daily observations over the past six months to compute the average stock price PRC , and $IVOL$ and $ISKEW$ (i.e., the idiosyncratic volatility and skewness based on the [Fama and French 2015](#) five-factor model); the gambling propensity GP equals 1 if in the cross-section, the PRC is in the bottom three deciles, the $IVOL$ is in the top three deciles, and the $ISKEW$ is in the top three deciles, and 0 otherwise. For a stock-month from July of a year to June of the next year, ADV is the industry-adjusted growth of the advertising expense computed using the annual report in the past fiscal year; ME is the stock's market value of equity as of the end of the past month; $Firm\ age$ is the number of months since the stock's first CRSP appearance as of the end of the past month; BM is the book-to-market ratio computed using the book equity as of the end of the past fiscal year, and the market value of equity as of the end of the past calendar year; D/A is the stock's book debt divided by total assets as of the end of the past fiscal year; $EVOLA$ is the earnings volatility of the stock computed as the standard deviation of EPS using at least 10 quarters in the past 20 quarters; ANA is the number of analysts who follow the firm and report forecasts to the I/B/E/S database in the past month; $FDISP$ is the stock's analyst forecast dispersion in the past month; and AT is the turnover-based [Amihud \(2002\)](#) illiquidity measure computed as the average of the ratio of the daily absolute return to daily turnover using at least 90 daily data in the past six months. To address extreme values, we winsorize the continuous variables (except $r_{j,t}$) at the 1% and 99% levels, using each of their distributions every month. Table 4 presents the time-series averages of the cross-sectional statistics of the variables. The sample period is from January 1977 to December 2024. See Appendix B for variable definitions.

	Mean	Median	SD	Percentile			
				10th	25th	75th	90th
TO	0.11	0.071	0.134	0.014	0.033	0.132	0.235
$r_{j,t}$	0.011	0.003	0.147	-0.132	-0.059	0.068	0.154
SUE	0.962	0.702	2.377	-1.21	-0.087	1.987	3.694
$Profitability$	0.088	0.079	0.079	0.011	0.039	0.128	0.186
PRC	61.828	15.905	1966.59	2.863	6.56	32.589	56.596
$IVOL$	0.029	0.024	0.021	0.012	0.016	0.036	0.051
$ISKEW$	0.478	0.348	1.442	-0.737	-0.101	0.925	1.863
GP	0.087	0	0.281	0	0	0	0.146
ADV	-0.001	-0.057	0.82	-0.756	-0.299	0.25	0.797
ME (\$10 ⁶)	3012.953	384.588	8742.633	26.495	85.497	1618.641	6538.849
$Firm\ Age$	181.317	146.028	138.088	28.306	71.888	261.95	390.499
BM	0.802	0.673	0.598	0.208	0.383	1.048	1.51
D/A	0.233	0.193	0.209	0.007	0.056	0.354	0.514
$EVOLA$	0.52	0.268	0.799	0.075	0.136	0.556	1.124
ANA	1.827	0.167	3.478	0	0	2.14	6.008
$FDISP$	0.145	0.08	0.198	0.019	0.038	0.165	0.327
AT	71.591	17.221	176.915	3.894	6.727	55.622	157.632

Table 5: Gambling propensity and turnover

The table presents the estimated coefficients and the corresponding t -statistics (in parentheses) for the following regression:

$$TO_{j,t} = b_0 + b_1 \times GP_{j,t} + b_2 \times Controls + \epsilon_{j,t}.$$

$TO_{j,t}$ is the turnover of the j 'th stock in month t . GP equals 1 if in the past six months, the average stock price (PRC) is in the bottom three deciles and the idiosyncratic volatility ($IVOL$) and skewness ($ISKEW$) are both in the top three deciles in the cross-section, and 0 otherwise. We control for past stock returns in months $t-1$, $t-2$, $t-12$ to $t-3$ ($r_{j,t-1}$, $r_{j,t-2}$, and $r_{j,t-12 \text{ to } t-3}$), market equity (ME), firm age, book-to-market ratio (BM), leverage (D/A), earnings volatility ($EVOLA$), the number of analysts following the firm and reporting forecasts (ANA), analyst forecast dispersion ($FDISP$), and illiquidity (AT). To address extreme values, we winsorize the continuous variables at the 1% and 99% levels, using each of their distributions every month. We estimate the regression using the Fama-MacBeth procedure and correct the standard errors using the Newey-West method with up to three lags. *, ** and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 1977 to December 2024. See Appendix B for variable definitions.

Dependent variable: $TO_{j,t} \times 100$		
	(1)	(2)
GP	3.925*** (6.46)	2.065*** (5.80)
$r_{j,t-1}$	1.173 (1.53)	0.710 (1.07)
$r_{j,t-2}$	-0.030 (-0.04)	0.909 (1.51)
$r_{j,t-12 \text{ to } t-3}$	1.028*** (3.15)	2.264*** (7.63)
$\ln(ME)$	0.986*** (9.14)	-0.537*** (-7.33)
$\ln(Firm \text{ age})$	-1.264*** (-16.71)	-0.957*** (-15.58)
BM	-1.191*** (-9.34)	-1.885*** (-11.17)
D/A	1.970*** (7.65)	1.106*** (3.95)
$EVOLA$	1.174*** (12.30)	0.826*** (11.94)
$\ln(1 + ANA)$		2.620*** (16.72)
$FDISP$		9.715*** (12.51)
AT	-0.023*** (-8.36)	-0.096*** (-5.50)
Observations	1,891,323	958,356
R-squared	0.196	0.214

Table 6: Gambling propensity and the PEAD: Portfolio analysis

For each stock in month t , we use the quarterly report announced in the past three months to compute the earnings surprise (SUE). GP equals 1 if in the past six months, the average stock price (PRC) is in the bottom three deciles and the idiosyncratic volatility ($IVOL$) and skewness ($ISKEW$) are both in the top three deciles in the cross-section, and 0 otherwise. In the month, we divide the sample stocks into two equal groups based on SUE , and independently into two groups based on GP ; this leads to 2×2 portfolios. We compute the return of each portfolio by weighting stocks in the portfolio equally. This table presents the excess return over the risk-free interest rate (Exret), and benchmark-adjusted returns based on the CAPM, the Fama and French (1993) and Carhart (1997) 4-factor model (FFC4), and the Fama and French (2015) 5-factor model (FF5) for each portfolio, as well as each high- SUE minus low- SUE (conditional on GP) portfolio, and the return difference between high- SUE minus low- SUE portfolios conditional on $GP = 1$ and $GP = 0$. We correct standard errors using the Newey-West method with up to three lags. t -statistics are reported in parentheses. *, ** and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 1977 to December 2024. See Appendix B for variable definitions.

<i>Risk-adjusted return $\times 100$</i>									
	Exret			CAPM		FFC4		FF5	
	All	$GP = 0$	$GP = 1$	$GP = 0$	$GP = 1$	$GP = 0$	$GP = 1$	$GP = 0$	$GP = 1$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Low SUE	0.657*** (2.51)	0.677*** (2.7)	0.331 (0.91)	-0.128 (-0.98)	-0.608** (-2.13)	-0.061 (-0.96)	-0.468** (-2.35)	-0.119* (-1.78)	-0.312 (-1.57)
(2) High SUE	1.14*** (5.63)	1.118*** (5.56)	1.759*** (5.28)	0.437*** (4.26)	0.929*** (3.36)	0.341*** (6.2)	0.899*** (4.12)	0.238*** (5.62)	0.934*** (4.36)
(2)-(1)	0.484*** (4.46)	0.441*** (4.64)	1.429*** (7.4)	0.566*** (6.01)	1.537*** (7.62)	0.402*** (5.07)	1.367*** (6.96)	0.357*** (5.28)	1.246*** (6.6)
Difference			0.988*** (5.55)		0.971*** (5.3)		0.965*** (5.17)		0.889*** (4.81)

Table 7: Gambling propensity and the PEAD: Regression analysis

This table reports the estimated coefficients and the corresponding t -statistics (in parentheses) for the regression

$$\text{Risk-adjusted return}_{j,t} = b_0 + b_1 \times SUE_{j,t} + b_2 \times SUE_{j,t} \times GP_{j,t} + b_3 \times GP_{j,t} + b_4 \times \text{Controls} + \epsilon_{j,t}.$$

For the j 'th stock in month t , $\text{Risk-adjusted return}_{j,t}$ is the excess return over the risk-free interest rate (Exret) or the benchmark-adjusted returns based on the CAPM, the [Fama and French \(1993\)](#) and [Carhart \(1997\)](#) 4-factor model (FFC4), and the [Fama and French \(2015\)](#) 5-factor model (FF5). We use the quarterly report announced in the past three months to compute the earnings surprise (SUE). GP equals 1 if in the past six months, the average stock price (PRC) is in the bottom three deciles and the idiosyncratic volatility ($IVOL$) and skewness ($ISKEW$) are both in the top three deciles in the cross-section, and 0 otherwise. We control for past stock returns in months $t-1$, $t-2$, $t-12$ to $t-3$ ($r_{j,t-1}$, $r_{j,t-2}$, and $r_{j,t-12 \text{ to } t-3}$), market equity (ME), book-to-market ratio (BM), and illiquidity (AT). To address extreme values, we winsorize all continuous variables (except the dependent variable) at the 1% and 99% levels, using each of their distributions every month. We estimate the regression using the Fama-MacBeth procedure and correct the standard errors using the Newey-West method with up to three lags. *, ** and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 1977 to December 2024. See Appendix B for variable definitions.

Dependent variable: $\text{Risk-adjusted return}_{j,t} \times 100$								
	Exret (1)	Exret (2)	CAPM (3)	CAPM (4)	FFC4 (5)	FFC4 (6)	FF5 (7)	FF5 (8)
SUE	0.100*** (4.95)	0.109*** (6.72)	0.125*** (7.53)	0.131*** (10.00)	0.099*** (6.97)	0.123*** (9.99)	0.086*** (6.46)	0.116*** (10.30)
$SUE \times GP$	1.045*** (5.59)	0.921*** (4.61)	1.051*** (5.83)	0.901*** (4.99)	1.104*** (4.85)	1.014*** (4.34)	1.111*** (4.70)	1.069*** (4.39)
GP	-0.115 (-0.53)	-0.221 (-1.30)	-0.287 (-1.44)	-0.364** (-2.35)	-0.290* (-1.72)	-0.310** (-2.08)	-0.225 (-1.30)	-0.220 (-1.43)
$r_{j,t-1}$		-3.641*** (-9.58)		-3.740*** (-9.03)		-5.155*** (-8.76)		-5.795*** (-10.34)
$r_{j,t-2}$		-0.130 (-0.38)		0.018 (0.05)		-0.949** (-2.09)		-0.991** (-2.17)
$r_{j,t-12 \text{ to } t-3}$		0.607*** (3.62)		0.620*** (3.91)		0.383** (2.41)		0.201 (1.19)
$\ln(ME)$		-0.085*** (-2.75)		-0.089*** (-2.84)		-0.074*** (-3.62)		-0.093*** (-4.43)
BM		0.164* (1.83)		0.211** (2.38)		0.132* (1.83)		-0.013 (-0.18)
AT		0.001 (1.47)		0.001*** (3.07)		0.001** (2.19)		0.001 (1.47)
Observations	1,641,628	1,560,739	1,641,628	1,560,739	1,641,628	1,560,739	1,641,628	1,560,739
R-squared	0.012	0.050	0.011	0.044	0.009	0.039	0.008	0.041

Table 8: Gambling propensity and the post-profitability-announcement drift

This table reports the estimated coefficients and the corresponding t -statistics (in parentheses) for the regression

$$Risk\text{-}adjusted\ return_{j,t} = b_0 + b_1 \times Profitability_{j,t} + b_2 \times Profitability_{j,t} \times GP_{j,t} + b_3 \times GP_{j,t} + b_4 \times Controls + \epsilon_{j,t}.$$

For the j 'th stock in month t , $Risk\text{-}adjusted\ return_{j,t}$ is the excess return over the risk-free interest rate (Exret) or the benchmark-adjusted returns based on the CAPM, the [Fama and French \(1993\)](#) and [Carhart \(1997\)](#) 4-factor model (FFC4), and the [Fama and French \(2015\)](#) 5-factor model (FF5). We use the quarterly report released in the past three months to compute gross margins ($Profitability$). GP equals 1 if in the past six months, the average stock price (PRC) is in the bottom three deciles and the idiosyncratic volatility ($IVOL$) and skewness ($ISKEW$) are both in the top three deciles in the cross-section, and 0 otherwise. We control for past stock returns in months $t-1$, $t-2$, $t-12$ to $t-3$ ($r_{j,t-1}$, $r_{j,t-2}$, and $r_{j,t-12\ to\ t-3}$), market equity (ME), book-to-market ratio (BM), and illiquidity (AT). To address extreme values, we winsorize all continuous variables (except the dependent variable) at the 1% and 99% levels, using each of their distributions every month. We estimate the regression using the Fama-MacBeth procedure and correct the standard errors using the Newey-West method with up to three lags. *, ** and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 1977 to December 2024. See Appendix B for variable definitions.

Dependent variable: $Risk\text{-}adjusted\ return_{j,t} \times 100$								
	Exret (1)	Exret (2)	CAPM (3)	CAPM (4)	FFC4 (5)	FFC4 (6)	FF5 (7)	FF5 (8)
$Profitability$	3.666*** (7.17)	3.777*** (7.73)	3.793*** (7.87)	3.936*** (8.13)	3.647*** (7.19)	4.115*** (7.86)	2.979*** (6.46)	3.438*** (7.22)
$Profitability \times GP$	7.737*** (5.32)	6.816*** (4.66)	8.009*** (5.38)	7.142*** (4.77)	6.074*** (4.05)	5.767*** (3.79)	6.785*** (4.77)	7.027*** (4.53)
GP	-0.857*** (-3.36)	-0.797*** (-4.15)	-1.080*** (-4.51)	-0.952*** (-5.25)	-0.950*** (-4.39)	-0.824*** (-4.61)	-0.934*** (-4.58)	-0.823*** (-4.52)
$r_{j,t-1}$		-3.543*** (-8.87)		-3.641*** (-8.36)		-5.141*** (-8.42)		-5.754*** (-9.84)
$r_{j,t-2}$		0.073 (0.21)		0.236 (0.69)		-0.778* (-1.67)		-0.821* (-1.74)
$r_{j,t-12\ to\ t-3}$		0.637*** (3.56)		0.645*** (3.89)		0.401** (2.38)		0.233 (1.30)
$\ln(ME)$		-0.040 (-1.16)		-0.031 (-0.91)		-0.019 (-0.81)		-0.037 (-1.55)
BM		0.340*** (3.62)		0.383*** (4.19)		0.300*** (3.93)		0.119 (1.46)
AT		0.001** (2.19)		0.002*** (3.62)		0.001*** (2.76)		0.001** (2.17)
Observations	1,627,406	1,538,391	1,627,406	1,538,391	1,627,406	1,538,391	1,627,406	1,538,391
R-squared	0.011	0.048	0.010	0.043	0.009	0.042	0.008	0.042

Table 9: Gambling propensity, advertising, and risk-adjusted returns

The table presents the estimated coefficients and the corresponding t -statistics (in parentheses) for the following regression:

$$Risk\text{-}adjusted\ return_{j,t} = b_0 + b_1 \times ADV_{j,t} + b_2 \times ADV_{j,t} \times GP_{j,t} + b_3 \times GP_{j,t} + b_4 \times Controls + \epsilon_{j,t}.$$

For the j 'th stock in month t , $Risk\text{-}adjusted\ return_{j,t}$ is the excess return over the risk-free interest rate (Exret) or benchmark-adjusted returns based on the CAPM, the [Fama and French \(1993\)](#) and [Carhart \(1997\)](#) 4-factor model (FFC4), and the [Fama and French \(2015\)](#) 5-factor model (FF5). For a month t from July of a year to June of the next year, ADV is the industry-adjusted growth of the advertising expense computed using the annual report in the past fiscal year. GP equals 1 if in the past six months, the average stock price (PRC) is in the bottom three deciles and the idiosyncratic volatility ($IVOL$) and skewness ($ISKEW$) are both in the top three deciles in the cross-section, and 0 otherwise. We control for the earnings surprise (SUE) and gross margins ($Profitability$), and their interactions with GP , along with past stock returns in months $t - 1$, $t - 2$, $t - 12$ to $t - 3$ ($r_{j,t-1}$, $r_{j,t-2}$, and $r_{j,t-12\ to\ t-3}$), market equity (ME), book-to-market ratio (BM), and illiquidity (AT). To address extreme values, we winsorize all continuous variables (except the dependent variable $Risk\text{-}adjusted\ return_{j,t}$) at the 1% and 99% levels, using each of their distributions every month. We estimate the regression using the Fama-MacBeth procedure and correct the standard errors using the Newey-West method with up to three lags. *, ** and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 1977 to December 2024. See Appendix B for variable definitions.

Table 9 (continued)

Dependent variable: $Risk\text{-adjusted return}_{i,t} \times 100$												
	Exret (1)	Exret (2)	Exret (3)	CAPM (4)	CAPM (5)	CAPM (6)	FFC4 (7)	FFC4 (8)	FFC4 (9)	FF5 (10)	FF5 (11)	FF5 (12)
<i>ADV</i>	-0.085*** (-3.32)	-0.057** (-2.18)	-0.099*** (-3.20)	-0.103*** (-3.87)	-0.055** (-2.09)	-0.105*** (-3.34)	-0.079*** (-2.68)	-0.051* (-1.74)	-0.092*** (-2.65)	-0.047* (-1.72)	-0.008 (-0.28)	-0.051 (-1.47)
<i>ADV</i> $\times$ <i>GP</i>	-0.591*** (-2.91)	-0.535** (-2.04)	-0.395* (-1.78)	-0.563*** (-2.78)	-0.589** (-2.20)	-0.438* (-1.93)	-0.472** (-2.22)	-0.580* (-1.94)	-0.480* (-1.91)	-0.396* (-1.67)	-0.652** (-2.16)	-0.540** (-2.06)
<i>GP</i>	-0.572** (-2.31)	-0.057 (-0.27)	-0.835*** (-2.75)	-0.734*** (-3.33)	-0.205 (-1.04)	-0.925*** (-3.11)	-0.734*** (-3.53)	-0.147 (-0.72)	-0.944*** (-3.10)	-0.636*** (-2.93)	0.006 (0.03)	-1.018*** (-3.16)
<i>SUE</i>		0.108*** (5.84)			0.128*** (8.26)			0.109*** (7.86)			0.112*** (7.76)	
<i>SUE</i> $\times$ <i>GP</i>		0.679* (1.89)			0.669** (1.98)			0.630 (1.60)			0.829** (2.40)	
<i>Profitability</i>			3.652*** (6.66)			4.087*** (7.68)			4.047*** (7.07)			3.393*** (6.02)
<i>Profitability</i> $\times$ <i>GP</i>			5.275** (2.07)			5.115** (1.98)			5.129* (1.93)			7.335*** (2.64)
$r_{j,t-1}$		-3.663*** (-9.37)	-3.511*** (-8.25)		-3.860*** (-9.03)	-3.678*** (-7.95)		-5.301*** (-8.89)	-5.225*** (-8.31)		-5.875*** (-9.86)	-5.740*** (-9.18)
$r_{j,t-2}$		0.230 (0.59)	0.455 (1.17)		0.304 (0.82)	0.531 (1.38)		-0.614 (-1.20)	-0.465 (-0.90)		-0.714 (-1.37)	-0.602 (-1.12)
$r_{j,t-12 \text{ to } t-3}$		0.530*** (3.14)	0.557*** (2.94)		0.519*** (3.20)	0.519*** (2.91)		0.327** (1.97)	0.314* (1.65)		0.146 (0.81)	0.143 (0.71)
$\ln(ME)$		-0.060** (-2.07)	-0.023 (-0.67)		-0.070** (-2.34)	-0.014 (-0.41)		-0.047** (-2.17)	-0.001 (-0.05)		-0.061*** (-2.82)	-0.010 (-0.41)
<i>BM</i>		0.159 (1.60)	0.300*** (2.95)		0.201** (2.03)	0.340*** (3.43)		0.147 (1.65)	0.271*** (3.06)		0.066 (0.76)	0.124 (1.35)
<i>AT</i>		0.001* (1.94)	0.003*** (2.85)		0.002*** (2.99)	0.003*** (4.24)		0.001** (2.38)	0.003*** (3.17)		0.001** (2.14)	0.003*** (3.05)
Observations	793,021	581,994	514,673	793,021	581,994	514,673	793,021	581,994	514,673	793,021	581,994	514,673
R-squared	0.010	0.063	0.060	0.010	0.057	0.055	0.009	0.055	0.056	0.009	0.057	0.057

**Internet Appendix for
Asset Pricing with Gambling, Affect Investing, and Overconfidence:
Theory and Evidence**

IA.1 The Survey

Screening Questions

Before you start the survey, please answer the following questions, which will determine whether you are eligible to participate in this survey. Kindly note that only eligible participants can proceed to the survey and receive compensation.

1. Do you have a brokerage account?
 - A. Yes
 - B. No
2. Do you currently have any investments in the stock market?
 - A. Yes
 - B. No

Survey questions

1. When an investor buys and holds shares of a company, what do they own?
 - A. A guaranteed portion of the company's profits every year
 - B. A loan that the company must repay with interest
 - C. A partial ownership stake in the company
 - D. The right to use the company's products at a discount
 - E. Do not know
 - F. Prefer not to answer
2. When you hold a company's stock, what kind of payoff might you receive?
 - A. Fixed interest payments at regular intervals
 - B. Potential dividends and capital gains if price rises
 - C. Guaranteed repayment of the money you invested at maturity
 - D. Rental income from the company's physical assets

- E. Do not know
 - F. Prefer not to answer
3. For how many years have you been investing in the stock market?
- A. Less than 1 year
 - B. 1–3 years
 - C. 4–6 years
 - D. 7–10 years
 - E. More than 10 years
 - F. Prefer not to answer
4. When you make investments in the stock market. How likely do you believe your investment returns will be above the market average over the next 12 months?
- A. Very likely
 - B. Likely
 - C. Neutral
 - D. Unlikely
 - E. Very unlikely
 - F. Do not know
 - G. Prefer not to answer
5. How would you rate your ability to pick winning stocks?
- A. Much better than average
 - B. Slightly better than average
 - C. About average
 - D. Slightly worse than average
 - E. Much worse than average
 - F. Do not know

- G. Prefer not to answer
6. Do you agree with the following statement? One of the reasons I buy certain stocks is because I receive positive information about them from public sources (e.g., earnings announcements).
- A. Strongly agree
 - B. Agree
 - C. Neutral
 - D. Disagree
 - E. Strongly disagree
 - F. Do not know
 - G. Prefer not to answer
7. Do you agree with the following statement? When trading stocks, I tend to view them like lotteries; I am comfortable accepting small losses if they offer the chance of a big gain.
- A. Strongly agree
 - B. Agree
 - C. Neutral
 - D. Disagree
 - E. Strongly disagree
 - F. Do not know
 - G. Prefer not to answer
8. Do you agree with the following statement? When I trade stocks, I enjoy the excitement and thrill.
- A. Strongly agree
 - B. Agree

- C. Neutral
 - D. Disagree
 - E. Strongly disagree
 - F. Do not know
 - G. Prefer not to answer
9. Do you agree with the following statement? When I trade stocks, my decisions are influenced by my perceptions of and familiarity with the company's products.
- A. Strongly agree
 - B. Agree
 - C. Neutral
 - D. Disagree
 - E. Strongly disagree
 - F. Do not know
 - G. Prefer not to answer
10. Do you agree with the following statement? When I trade stocks, I tend to invest in companies that share my values and principles.
- A. Strongly agree
 - B. Agree
 - C. Neutral
 - D. Disagree
 - E. Strongly disagree
 - F. Do not know
 - G. Prefer not to answer
11. How likely are you to trade stocks based on a fundamental analysis of a firm (e.g., using past financials or a cash flow model)?

- A. Very likely
 - B. Likely
 - C. Neutral
 - D. Unlikely
 - E. Very unlikely
 - F. Do not know
 - G. Prefer not to answer
12. How likely are you to trade stocks because you need to rebalance/diversify your portfolio?
- A. Very likely
 - B. Likely
 - C. Neutral
 - D. Unlikely
 - E. Very unlikely
 - F. Do not know
 - G. Prefer not to answer
13. What is your household's total annual income (before taxes)?
- A. Less than \$20,000
 - B. \$20,000 – \$39,999
 - C. \$40,000 – \$59,999
 - D. \$60,000 – \$79,999
 - E. \$80,000 – \$99,999
 - F. \$100,000 – \$149,999
 - G. \$150,000 – \$199,999
 - H. \$200,000 or more

I. Prefer not to answer

14. What is your household's total net worth (total assets minus total liabilities)?

- A. Less than \$50,000
- B. \$50,000 – \$99,999
- C. \$100,000 – \$249,999
- D. \$250,000 – \$499,999
- E. \$500,000 – \$999,999
- F. \$1,000,000 – \$1,999,999
- G. \$2,000,000 or more
- H. Prefer not to answer

15. What is your household's total investment in the stock market?

- A. Less than \$10,000
- B. \$10,000 – \$49,999
- C. \$50,000 – \$99,999
- D. \$100,000 – \$249,999
- E. \$250,000 – \$499,999
- F. \$500,000 – \$999,999
- G. \$1,000,000 or more
- H. Prefer not to answer

16. Which of the following best describes the industry in which you are currently employed (or most recently employed)?

- A. Finance / Banking / Insurance
- B. Technology / Information Technology
- C. Manufacturing / Engineering
- D. Retail / Wholesale / Consumer Goods

- E. Healthcare / Pharmaceuticals / Life Sciences
- F. Education / Research
- G. Public Sector / Government / Nonprofit
- H. Energy / Utilities
- I. Real Estate / Construction
- J. Hospitality / Tourism / Food Services
- K. Transportation / Logistics
- L. Other (please specify)
- M. Not currently employed
- N. Prefer not to answer

17. What is the highest level of education you have completed?

- A. No formal education / Primary school
- B. Secondary school / High school
- C. Diploma / Technical or vocational training
- D. Bachelor's degree
- E. Master's degree
- F. Doctoral degree
- G. Others
- H. Prefer not to answer

IA.2 Heterogenous Overconfidence in the Cross-section of Stocks

In the main paper (Section 3.1), we have assumed that in the cross section, *OAG* investors underestimate the precision of the public signal $s_j = \theta_j + \epsilon_j$ about the firm-specific cash flow θ_j to the same extent; specifically, they believe that ϵ_j has a larger variance $\rho\nu_{\epsilon_j}$ than the actual variance ν_{ϵ_j} , where $\rho > 1$ is a constant parameter. Here, we consider a variation in which the degree to which *OAG* investors underestimate the precision of public signals varies with j . Specifically, *OAG* investors believe that ϵ_j has a variance $\rho_j\nu_{\epsilon_j}$, where $\rho_j > 1$ is a constant parameter and it can be that $\rho_j \neq \rho_{j'} \forall j \neq j'$. Denote the skeptical belief about the variance of s_j as $\hat{\nu}_{s_j} = \nu_{\theta_j} + \rho_j\nu_{\epsilon_j}$.

As in the main paper, we still assume that *OAG* investors underestimate the precision of public information $\tau = F + \zeta$ about the common factor F , in that they believe that ζ has a larger variance $\rho\nu_{\zeta}$ than the actual variance ν_{ζ} , where $\rho > 1$ is a constant parameter. We can use the same derivation as in the main paper to show that the equilibrium stock prices take the same form as in Theorem 1. We are primarily interested in the interaction between the gambling and the overconfidence biases in the cross section. However, the setting here does not permit a closed-form analysis. Therefore, we use numerical analysis in what follows. As in the main paper (Section 3.2.2), we consider an economy with $J = 200$ stocks, where the G_j values are evenly distributed on the support $[0, 0.5]$. We assume that the ρ_j values are evenly distributed on the support $[2, 12]$. For simplicity, we let $A_j = 0 \forall j$. The other parameter values are $\gamma = 2$ and $\eta = 0.5$; $\forall j \ell_j = 1$, $\nu_{\theta_j} = 1$, $\nu_{\epsilon_j} = \nu_{\theta_j}/2$, and $\nu_{\xi_j} = 0.01$; $\nu_F = 0.01$ and $\nu_{\zeta} = \nu_F/2$; and the overconfidence parameter for the common factor, $\rho = 9$.

Figure IA.1 plots the expected turnover $E(T_j)$ as a function of gambling propensity G_j and the overconfidence parameter ρ_j . As in Figure 1 in the main paper, we assume that investors' endowments equal the ex ante means of their optimal demands (i.e., $\forall j Y_{OAG,j} = E(X_{OAG,j})$ and $Y_{Rational,j} = E(X_{Rational,j})$). We observe that as *OAG* investors underestimate the precision of the firm specific signals to a greater extent (i.e., a higher ρ_j), $E(T_j)$ increases.

Figure IA.2 plots the level of underreaction to public announcements (as measured by $\text{Cov}(r_j, S_j)$) as a function of gambling propensity G_j and the overconfidence parameter

ρ_j . Consistent with Figure 3 in the main paper, $\text{Cov}(r_j, S_j) > 0$. Also, in the cross section of stocks, as *OAG* investors underestimate the precision of the firm-specific signals to a greater extent (i.e., a higher ρ_j), the drift becomes more pronounced (i.e., a more positive $\text{Cov}(r_j, S_j)$). It can also be seen that when gambling propensity G_j is high, the positive relation between $\text{Cov}(r_j, S_j)$ and ρ_j becomes more pronounced.

Figure IA.3 plots the risk-adjusted expected return α_j for each stock as a function of the gambling propensity G_j and the overconfidence parameter ρ_j . We can see that in the cross section of stocks, as overconfidence investors underestimate the signals to a greater extent (i.e., a higher ρ_j), α_j increases. We also observe that when gambling propensity G_j is high, the positive relationship between α_j and ρ_j becomes more pronounced.

IA.3 A Traditional Form of Overconfidence

So far, we have assumed that both the signal about the common factor, τ , and the signal about the j 'th ($j = 1, \dots, J$) stock's firm-specific cash flow, s_j , are public information; and that *OAG* investors are skeptical about the quality of the information since they do not produce the information themselves (Odean 1998; Luo, Subrahmanyam, and Titman 2021).

Here we modify the setting in Section 3.1 of the main paper by assuming the presence of private information. Specifically, we assume that for the j 'th stock, *OAG* investors also observe a private signal, $s_j^* = \theta_j + \iota_j$, where the noise term ι_j is drawn from a normal distribution with zero mean and variance ν_{ι_j} . Further, we add a traditional form of overconfidence as in Daniel, Hirshleifer, and Subrahmanyam (1998). Specifically, *OAG* investors overestimate the precision of the private signal, $s_j^* = \theta_j + \iota_j$, in that they believe that ι_j has a smaller variance ν_{ι_j}/ρ^* than the actual variance ν_{ι_j} , where $\rho^* > 1$ is a constant parameter representing the scale of the traditional overconfident bias. We denote the unbiased (overconfident) belief about the variance of s_j^* as $\nu_{s_j^*} = \nu_{\theta_j} + \nu_{\iota_j}$ ($\omega_{s_j^*} = \nu_{\theta_j} + \nu_{\iota_j}/\rho^*$). Rational investors hold unbiased beliefs about the variance ν_{ι_j} . For simplicity, we still assume that *OAG* investors underestimate the precision of the public signal about the common factor, τ , and the precision of the public signal about the firm-specific cash flow, s_j , to the same extent as indicated by the constant parameter $\rho > 1$.

Denote the vector of the private signals as

$$s^* = \begin{pmatrix} s_1^* \\ s_2^* \\ \vdots \\ s_J^* \end{pmatrix}; \text{ and let } \mathcal{S} = \begin{pmatrix} s \\ s^* \end{pmatrix}.$$

Note that the per capita supply of each stock is fixed at unity. Stock prices fully reveal the private signals s^* ; therefore, there is no asymmetric information. However, investors have heterogeneous assessments of signal informativeness; that is, they agree to disagree. Specifically, *OAG* investors believe that $\theta|\mathcal{S} \sim N(\hat{q}\mathcal{S}, \hat{\Gamma})$, where $\hat{q}$ and $\hat{\Gamma}$ are constants depending on the variance-covariance matrix of θ and $\mathcal{S}$ based on *OAG* investors' biased beliefs. Rational investors believe that $\theta|\mathcal{S} \sim N(q\mathcal{S}, \Gamma)$, where q and Γ are constants depending on the variance-covariance matrix of θ and $\mathcal{S}$ based on their unbiased beliefs.

See Equations (1) and (2) of the main paper; we redefine the following parameters:

$$\begin{aligned} \Omega &\equiv \hat{q} - q, \quad \phi_{OAG} \equiv \ell\ell'\hat{\nu}_{F|\tau} + \hat{\Gamma} + \nu_\xi - G/\gamma, \quad \phi \equiv \ell\ell'\nu_{F|\tau} + \Gamma + \nu_\xi, \text{ and} \\ \Phi &\equiv \eta\phi_{OAG}^{-1} + (1 - \eta)\phi^{-1}. \end{aligned}$$

We obtain the following theorem (the proof of which is at the end of this Internet Appendix).

Theorem IA.1 *With overestimation of the precision of private information, in equilibrium:*

(i) *Stock prices are given by:*

$$P = \frac{1}{R_f} \left[\bar{V} + \ell \frac{\nu_F}{\nu_\tau} \tau + q\mathcal{S} + \Phi^{-1} \left[\eta\phi_{OAG}^{-1} (A + \ell\Delta\tau + \Omega\mathcal{S}) - \gamma\mathbf{1} \right] \right].$$

(ii) *Each OAG and rational investor's demands for the stocks are respectively given by:*

$$\begin{aligned} X_{OAG} &= \frac{\phi_{OAG}^{-1}}{\gamma} \left(A + \bar{V} + \ell \frac{\nu_F}{\hat{\nu}_\tau} \tau + \hat{q}\mathcal{S} - PR_f \right), \\ X_{Rational} &= \frac{\phi^{-1}}{\gamma} \left(\bar{V} + \ell \frac{\nu_F}{\nu_\tau} \tau + q\mathcal{S} - PR_f \right). \end{aligned}$$

We consider a simple economy like the one in Section 3.2.1 of the main paper, where firm-specific payoff variances are identical in the cross section of stocks (i.e., $\forall j \nu_{\theta_j} + \nu_{\xi_j} =$

ν), and signals about the firm-specific components θ_j , s_j , and s_j^* are uninformative (i.e., $\forall j \nu_{\epsilon_j}, \nu_{\iota_j} \rightarrow \infty$). In this case, we obtain the same analytical results as in Propositions 1, 2, and 3. In what follows, we examine the general case numerically as in Section 3.2.2 of the main paper.

IA.3.1 Turnover

We can use Theorem IA.1 to obtain the demand for the j 'th stock by each *OAG* and rational investor, denoted by $X_{OAG,j}$ and $X_{Rational,j}$, respectively, which are the j 'th elements of the vectors X_{OAG} and $X_{Rational}$. We can then use Equation (3) of the main paper to compute the expected turnover of the j 'th stock.

We consider an economy with $J = 200$ stocks, where the G_j values are evenly distributed on the support $[0, 0.5]$, and the A_j values are evenly distributed on the support $[-2, 2]$. The other parameter values are $\gamma = 2$ and $\eta = 0.5$; $\forall j \ell_j = 1$, $\nu_{\theta_j} = 1$, $\nu_{\epsilon_j} = \nu_{\iota_j} = \nu_{\theta_j}/2$, and $\nu_{\xi_j} = 0.01$; $\nu_F = 0.01$ and $\nu_\zeta = \nu_F/2$. The overconfidence parameter ρ takes values from 1 to 9. There is also a traditional form of overconfidence (as indicated by $\rho^* = 2$).¹

Figure IA.4 plots the expected turnover $E(T_j)$ for each stock as a function of gambling propensity G_j , for different values of overconfidence (ρ), ranging from 1 to 9. As in Figure 1 in the main paper, we assume here that each type of investors' endowments equal the ex ante means of their optimal demands (i.e., $\forall j Y_{OAG,j} = E(X_{OAG,j})$ and $Y_{Rational,j} = E(X_{Rational,j})$); in this case, the turnover is not affected by the affect parameter A_j . Figure IA.4 shows that when *OAG* investors correctly assess the precision of the public signals (i.e., $\rho = 1$), trading still occurs. This is caused by heterogeneous assessments of private information precision, due to *OAG* investors' traditional form of overconfidence (i.e., $\rho^* > 1$). Consistent with Figure 1, an increase in the gambling propensity G_j also leads to an increase in $E(T_j)$, and an increase in the overconfidence parameter ρ results in an increase in the expected turnover $E(T_j)$.

In Panel A of Figure IA.5, we assume that each investor's endowment equals the per

¹We set $\nu_{\iota_j} = \nu_{\theta_j}/2$ to indicate a significant magnitude of noise in the signal s_j^* . The traditional overconfidence parameter $\rho^* = 2$ is consistent with the range used in Odean (1998) (pp. 1909–10). See Footnote 13 of the main paper for justification of other parameter values.

capita supply (i.e., $\forall j, Y_{OAG,j} = Y_{Rational,j} = 1$); in Panel B, we assume that investor endowments are identically zero (i.e., $\forall j, Y_{OAG,j} = Y_{Rational,j} = 0$). We plot the expected turnover $E(T_j)$ for each stock as a function of the gambling propensity G_j and the affect parameter A_j . As in Figure 2 of the main paper, the cross-sectional relationship between $E(T_j)$ and A_j is non-monotonic; $E(T_j)$ is higher for stocks with extreme positive/negative values of A_j . Further, in the cross section of stocks, the expected turnover $E(T_j)$ increases as gambling propensity G_j increases.

IA.3.2 Underreaction to public information

Using Theorem IA.1, we can express the realized excess returns of the j 'th stock as

$$r_j = \mathbf{1}'_j(V - PR_f). \quad (\text{IA.1})$$

Recall that the public signal for the j 'th stock (see Equation (6) of the main paper) takes the following form:

$$S_j = \mu s_j + (1 - \mu)\tau,$$

where $\mu \in (0, 1]$ is a constant parameter. We can then use r_j from Equation (IA.1) to compute the underreaction measure $\text{Cov}(r_j, S_j)$.

Figure IA.6 plots $\text{Cov}(r_j, S_j)$, for each stock as a function of the gambling propensity G_j , for different levels of the overconfidence bias (ρ). We set $\mu = 0.8$ (our results are robust to different values of μ); the other parameters are the same as those used in the earlier figures. As in Figure 3 of the main paper, when *OAG* investors assess the precision of the signals properly (i.e., $\rho = 1$), we observe $\text{Cov}(r_j, S_j) = 0$ indicating no underreaction. However, if *OAG* investors underestimate the precision of the signals s and τ (i.e., $\rho > 1$), then $\text{Cov}(r_j, S_j) > 0$, and an increase in the gambling propensity G_j leads to an increase in $\text{Cov}(r_j, S_j)$. Also, if overconfident investors underestimate the precision of the signals to a greater extent (i.e., a higher ρ), $\text{Cov}(r_j, S_j)$ is higher.

IA.3.3 The (unconditional) risk-adjusted expected return

We represent the market excess return using the cross-sectional average of stock returns (see Equation IA.1):

$$r_M = \frac{1}{J} \mathbf{1}'(V - PR_f). \quad (\text{IA.2})$$

It follows from Equations (IA.1) and (IA.2) that the expected excess returns of the j 'th stock and the market can be expressed as

$$E(r_j) = \mathbf{1}'_j \Phi^{-1} (\gamma \mathbf{1} - \eta \phi_{OAG}^{-1} A), \text{ and } E(r_M) = \frac{1}{J} \mathbf{1}' \Phi^{-1} (\gamma \mathbf{1} - \eta \phi_{OAG}^{-1} A).$$

Note that these expected returns are unconditional on the public information τ and s , and the private information s^* . We can compute the (unconditional) risk-adjusted expected returns of the stocks as

$$\alpha_j = E(r_j) - \beta_{jM} E(r_M),$$

where $\beta_{jM} = \text{Cov}(r_j, r_M) / \text{Var}(r_M)$ for each stock.

Figure IA.7 plots the risk-adjusted return α_j as a function of gambling propensity G_j and affect parameter A_j . As in Figure 4 of the main paper, we observe that in the cross section of stocks, α_j decreases as the affect parameter A_j increases. Also the negative relationship between α_j and A_j becomes more pronounced when gambling propensity G_j is high.

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Proof of Theorem IA.1:

Denote $\mathcal{S} = \begin{pmatrix} s \\ s^* \end{pmatrix}$.

(a) The i 'th *OAG* investor believes that

$$F|\tau \sim N\left(\frac{\nu_F}{\hat{\nu}_\tau}\tau, \hat{\nu}_{F|\tau}\right) \quad \text{and} \quad \theta|\mathcal{S} \sim N\left(\hat{q}\mathcal{S}, \hat{\Gamma}\right),$$

where $\hat{q}$ and $\hat{\Gamma}$ are constants depending on the variance-covariance matrix of θ and $\mathcal{S}$ based on the investor's biased belief. Write the investor's wealth at Date 1 as

$$W_{i1} = W_{i0}R_f + X_i'(V - PR_f) = W_{i0}R_f + X_i'(\bar{V} + \ell F + \theta + \xi - PR_f).$$

The investor's demand X_i maximizes

$$\begin{aligned} U_{OAG}(W_{i1}^A, X_i) &= \hat{E}(W_{i1}^A|\tau, \mathcal{S}) - 0.5\gamma \hat{\text{Var}}(W_{i1}^A|\tau, \mathcal{S}) + C_G(X_i) \\ &= W_{i0}R_f + X_i' \left(A + \bar{V} + \ell \frac{\nu_F}{\hat{\nu}_\tau} \tau + \hat{q}\mathcal{S} - PR_f \right) - 0.5\gamma X_i' \phi_{OAG} X_i, \end{aligned}$$

where $\phi_{OAG} = \ell \ell' \hat{\nu}_{F|\tau} + \hat{\Gamma} + \nu_\xi - G/\gamma$. The f.o.c. w.r.t. X_i implies that the optimal demand is

$$X_{OAG} = \frac{\phi_{OAG}^{-1}}{\gamma} \left(A + \bar{V} + \ell \frac{\nu_F}{\hat{\nu}_\tau} \tau + \hat{q}\mathcal{S} - PR_f \right). \quad (\text{IA.3})$$

(b) The i 'th rational investor has unbiased beliefs that

$$F|\tau \sim N\left(\frac{\nu_F}{\nu_\tau}\tau, \nu_{F|\tau}\right), \quad \text{and} \quad \theta|\mathcal{S} \sim N(q\mathcal{S}, \Gamma),$$

where q and Γ are constants depending on the variance-covariance matrix of θ and $\mathcal{S}$ based on the investor's unbiased belief. We can use a similar derivation as in Part (a) of this proof to show that the demand is expressed as

$$X_{Rational} = \frac{\phi^{-1}}{\gamma} \left(\bar{V} + \ell \frac{\nu_F}{\nu_\tau} \tau + q\mathcal{S} - PR_f \right), \quad (\text{IA.4})$$

where $\phi = \ell \ell' \nu_{F|\tau} + \Gamma + \nu_\xi$.

(d) From Equations (IA.3) and (IA.4), the market-clearing condition $\eta X_{OAG} + (1 - \eta) X_{Rational} = \mathbf{1}$ implies that the equilibrium prices P take the form as given in this theorem. $\square$

Figure IA.1: Expected turnover, gambling propensity, and overconfidence bias in the cross section of stocks

This graph plots the expected turnover $E(T_j)$ for each stock as a function of gambling propensity G_j and the overconfidence parameter ρ_j . We consider an economy with $J = 200$ stocks, where the G_j values are evenly distributed on the support $[0, 0.5]$, and the ρ_j values are evenly distributed on the support $[2, 12]$. The other parameter values are $\gamma = 2$ and $\eta = 0.5$; $\forall j \ell_j = 1$, $\nu_{\theta_j} = 1$, $\nu_{\epsilon_j} = \nu_{\theta_j}/2$, and $\nu_{\xi_j} = 0.01$; $\nu_F = 0.01$ and $\nu_\zeta = \nu_F/2$; and the overconfidence parameter for the common factor, $\rho = 9$. We assume that each type of investors' endowments equal the ex ante means of their optimal demands (i.e., $\forall j Y_{OAG,j} = E(X_{OAG,j})$ and $Y_{Rational,j} = E(X_{Rational,j})$).

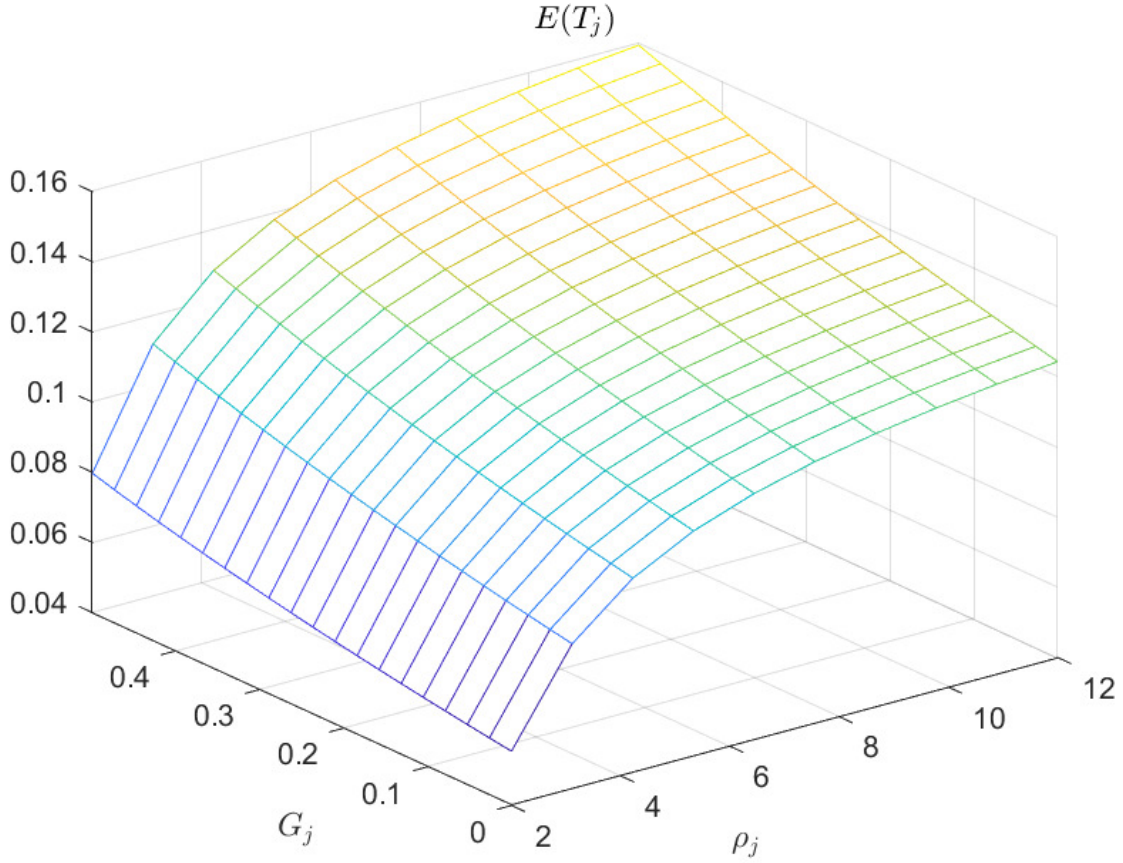


Figure IA.2: Level of underreaction to public information, gambling propensity, and overconfidence bias in the cross section of stocks

This graph plots the level of underreaction to public announcements (as measured by $\text{Cov}(r_j, S_j)$) for each stock for each stock as a function of gambling propensity G_j and the overconfidence parameter ρ_j . We consider an economy with $J = 200$ stocks, where the G_j values are evenly distributed on the support $[0, 0.5]$, and the ρ_j values are evenly distributed on the support $[2, 12]$. The other parameter values are $\gamma = 2$ and $\eta = 0.5$; $\forall j \ell_j = 1$, $\nu_{\theta_j} = 1$, $\nu_{\epsilon_j} = \nu_{\theta_j}/2$, and $\nu_{\xi_j} = 0.01$; $\nu_F = 0.01$ and $\nu_\zeta = \nu_F/2$; $\mu = 0.8$; and the overconfidence parameter for the the common factor, $\rho = 9$.

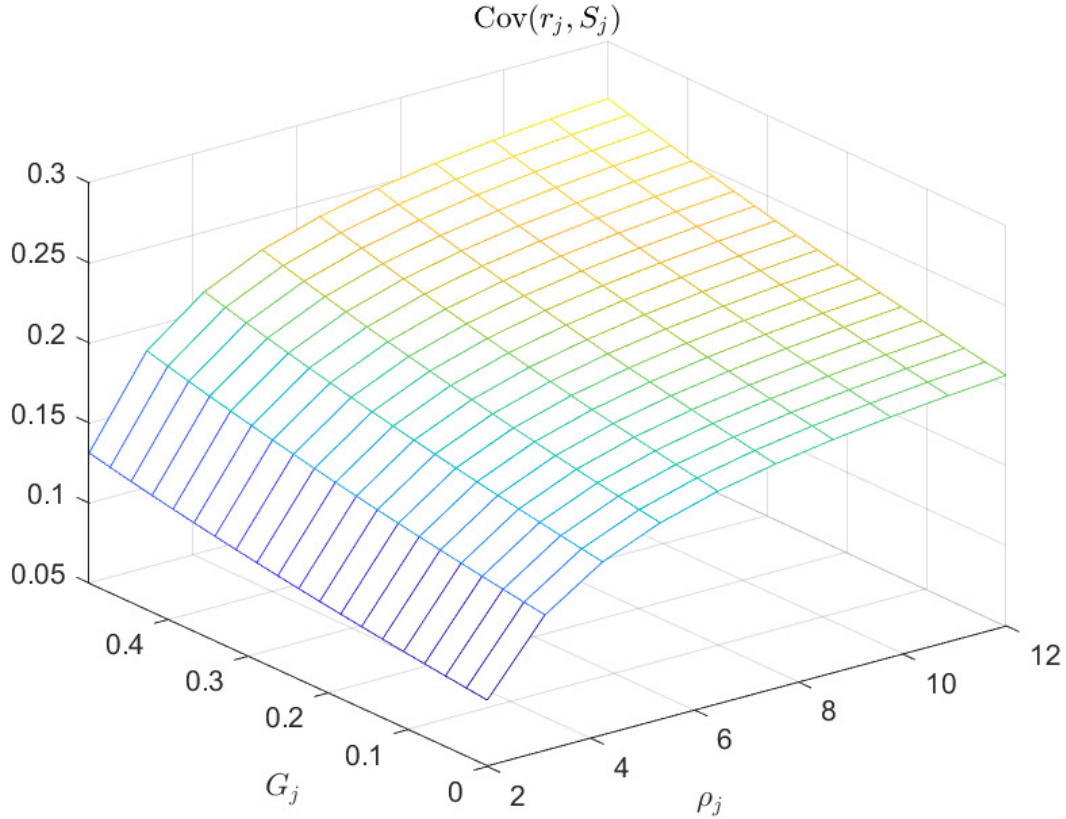


Figure IA.3: Risk-adjusted expected returns, gambling propensity, and overconfidence bias in the cross section of stocks

This graph plots the risk-adjusted expected return α_j for each stock as a function of the gambling propensity G_j and the overconfidence parameter ρ_j . We consider an economy with $J = 200$ stocks, where the G_j values are evenly distributed on the support $[0, 0.5]$, and the ρ_j values are evenly distributed on the support $[2, 12]$. The other parameter values are $\gamma = 2$ and $\eta = 0.5$; $\forall j$ $\ell_j = 1$, $\nu_{\theta_j} = 1$, $\nu_{\epsilon_j} = \nu_{\theta_j}/2$, and $\nu_{\xi_j} = 0.01$; $\nu_F = 0.01$ and $\nu_{\zeta} = \nu_F/2$; and the overconfidence parameter for the common factor, $\rho = 9$.

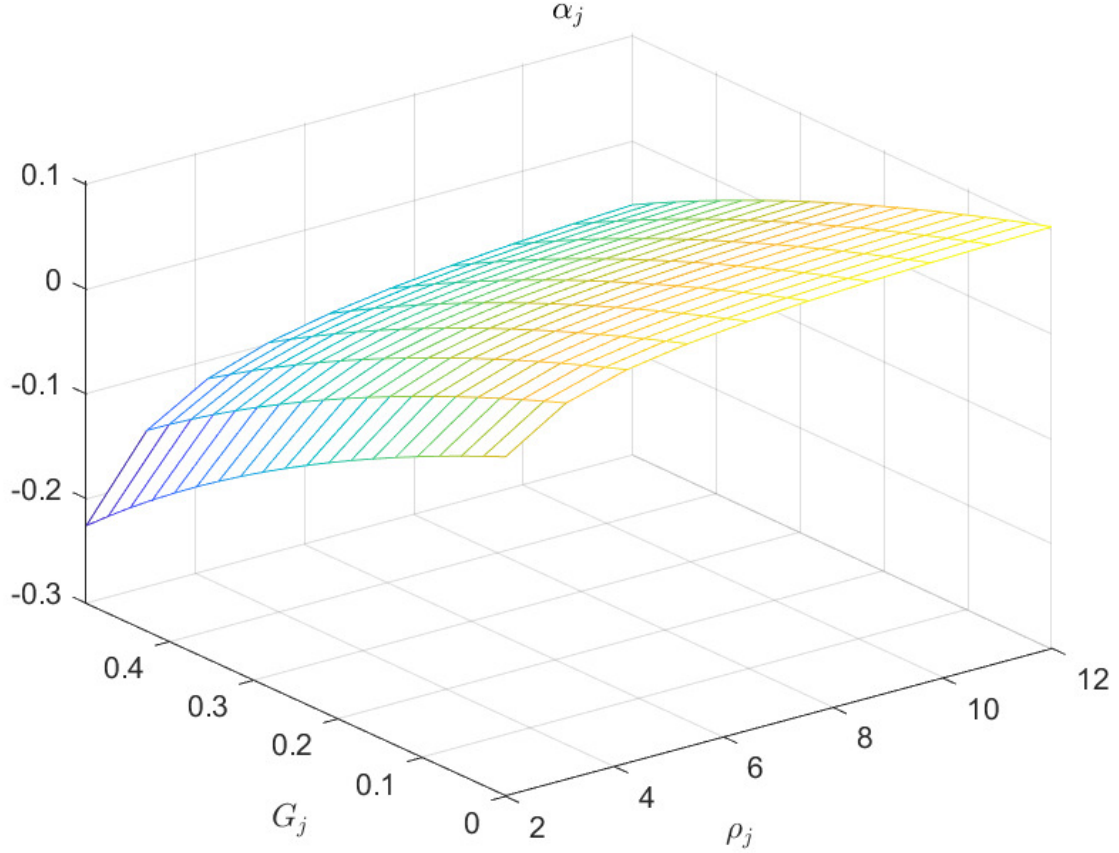


Figure IA.4: Expected turnover as a function of gambling propensity, for different levels of overconfidence, when there is private information

This graph plots the expected turnover $E(T_j)$ for each stock as a function of gambling propensity G_j , for different levels of the overconfidence bias (ρ). We consider an economy with $J = 200$ stocks, where the G_j values are evenly distributed on the support $[0, 0.5]$, and the A_j values are evenly distributed on the support $[-2, 2]$. The other parameter values are $\gamma = 2$ and $\eta = 0.5$; $\forall j \ell_j = 1$, $\nu_{\theta_j} = 1$, $\nu_{\epsilon_j} = \nu_{\iota_j} = \nu_{\theta_j}/2$, and $\nu_{\xi_j} = 0.01$; $\nu_F = 0.01$ and $\nu_\zeta = \nu_F/2$. There is also a traditional form of overconfidence (as indicated by $\rho^* = 2$). We assume that each type of investors' endowments equal the ex ante means of their optimal demands (i.e., $\forall j Y_{OAG,j} = E(X_{OAG,j})$ and $Y_{Rational,j} = E(X_{Rational,j})$).

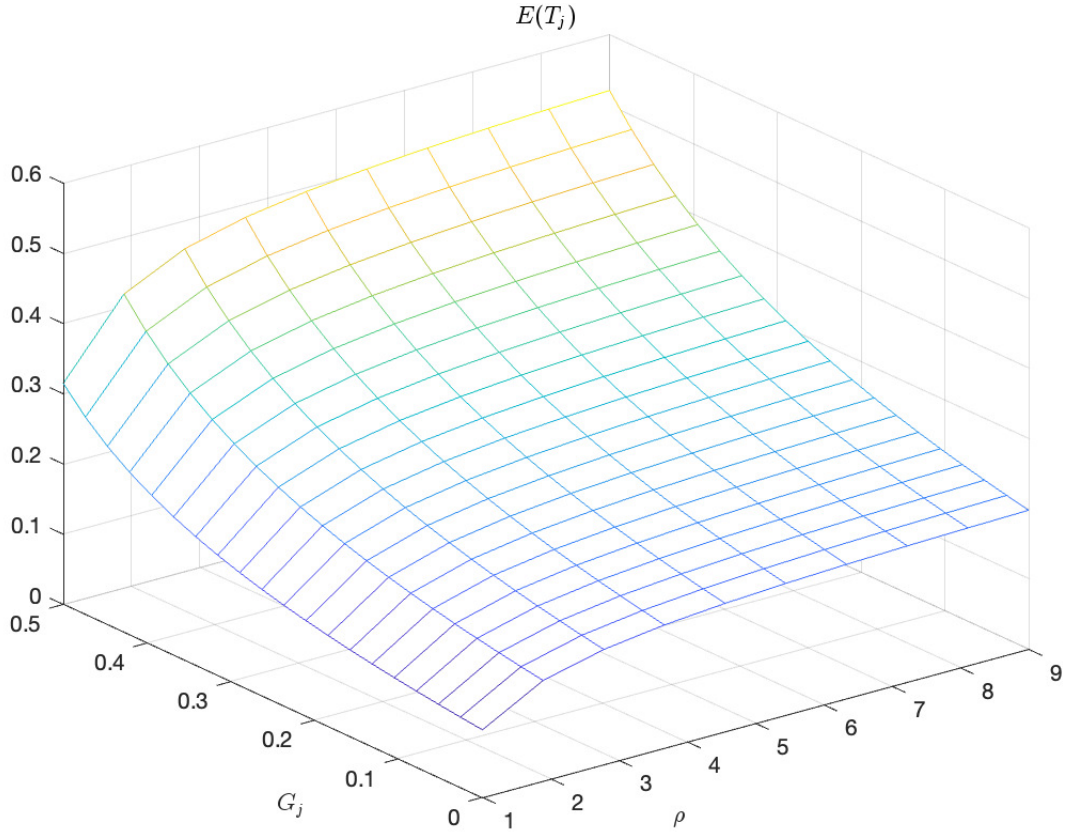


Figure IA.5: Expected turnover, gambling propensity, and the affect heuristic, when there is private information

This graph plots the expected turnover $E(T_j)$ for each stock as a function of the gambling propensity G_j and the affect parameter A_j . We consider an economy with $J = 200$ stocks, where the G_j values are evenly distributed on the support $[0, 0.5]$, and the A_j values are evenly distributed on the support $[-2, 2]$. The other parameter values are $\gamma = 2$ and $\eta = 0.5$; $\forall j \ell_j = 1$, $\nu_{\theta_j} = 1$, $\nu_{\epsilon_j} = \nu_{\theta_j}/2$, and $\nu_{\xi_j} = 0.01$; $\nu_F = 0.01$ and $\nu_\zeta = \nu_F/2$; and $\rho = 9$. There is also a traditional form of overconfidence (as indicated by $\rho^* = 2$). We assume that each type of investor's endowments equal per capita supplies (i.e., $\forall j Y_{OAG,j} = Y_{Rational,j} = 1$) in Panel A, and that all endowments equal zero (i.e., $\forall j Y_{OAG,j} = Y_{Rational,j} = 0$) in Panel B.

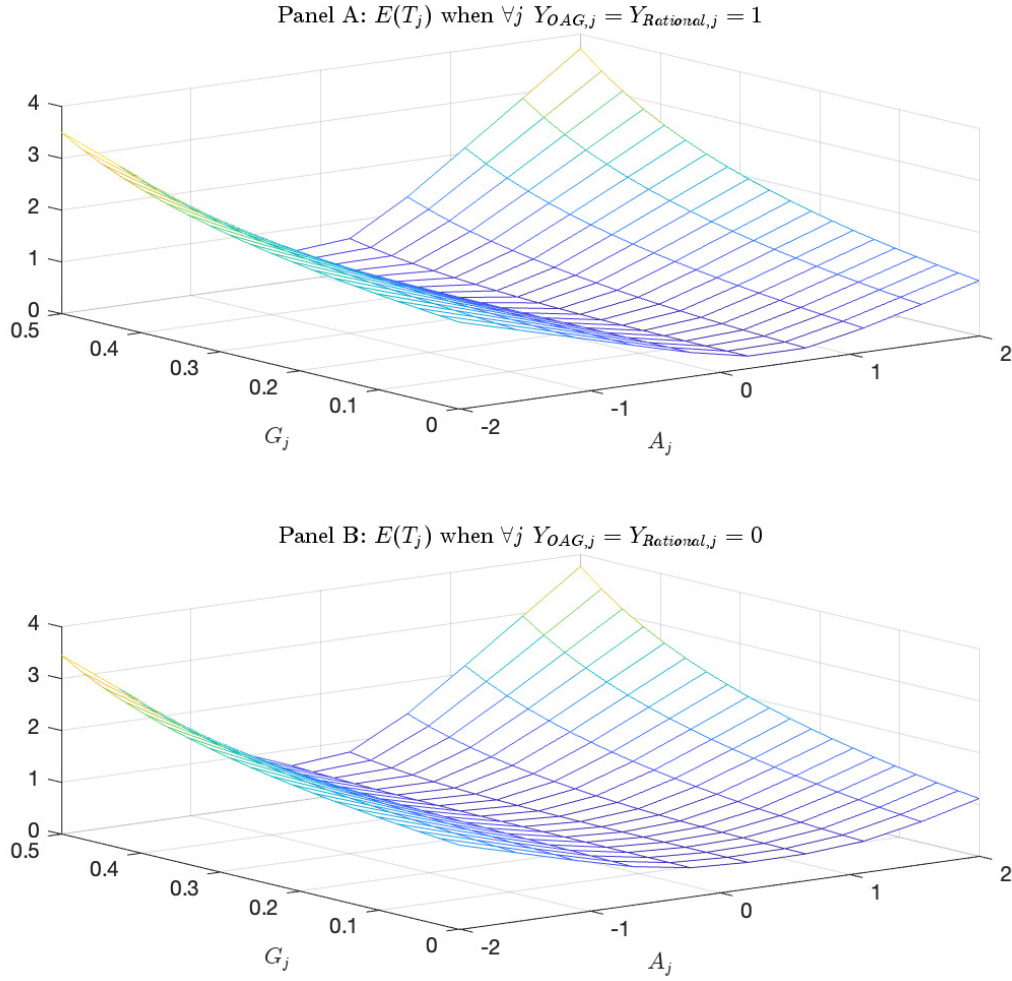


Figure IA.6: Level of underreaction to public information as a function of gambling propensity, for different levels of overconfidence, when there is private information. This graph plots the post-public-announcement drift (as measured by $\text{Cov}(r_j, S_j)$) for each stock as a function of the gambling propensity G_j , for different levels of the overconfidence bias (ρ). We consider an economy with $J = 200$ stocks, where the G_j values are evenly distributed on the support $[0, 0.5]$, and the A_j values are evenly distributed on the support $[-2, 2]$. The other parameter values are $\gamma = 2$ and $\eta = 0.5$; $\forall j \ell_j = 1$, $\nu_{\theta_j} = 1$, $\nu_{\epsilon_j} = \nu_{\iota_j} = \nu_{\theta_j}/2$, and $\nu_{\xi_j} = 0.01$; $\nu_F = 0.01$ and $\nu_\zeta = \nu_F/2$; and $\mu = 0.8$. There is also a traditional form of overconfidence (as indicated by $\rho^* = 2$).

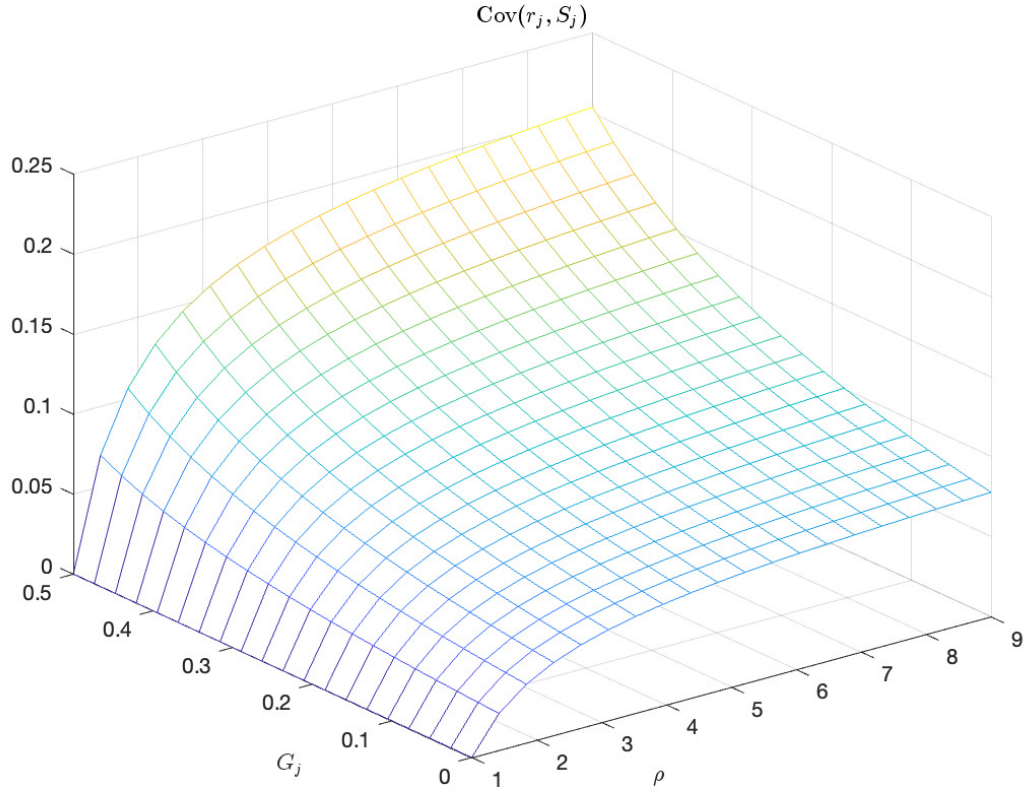


Figure IA.7: Risk-adjusted expected returns, gambling propensity, and the affect heuristic, when there is private information

This graph plots the risk-adjusted expected return α_j for each stock as a function of the gambling propensity G_j and the affect parameter A_j . We consider an economy with $J = 200$ stocks, where the G_j values are evenly distributed on the support $[0, 0.5]$, and the A_j values are evenly distributed on the support $[-2, 2]$. The other parameter values are $\gamma = 2$ and $\eta = 0.5$; $\forall j \ell_j = 1$, $\nu_{\theta_j} = 1$, $\nu_{\epsilon_j} = \nu_{\iota_j} = \nu_{\theta_j}/2$, and $\nu_{\xi_j} = 0.01$; $\nu_F = 0.01$ and $\nu_\zeta = \nu_F/2$; and $\rho = 9$. There is also a traditional form of overconfidence (as indicated by $\rho^* = 2$).

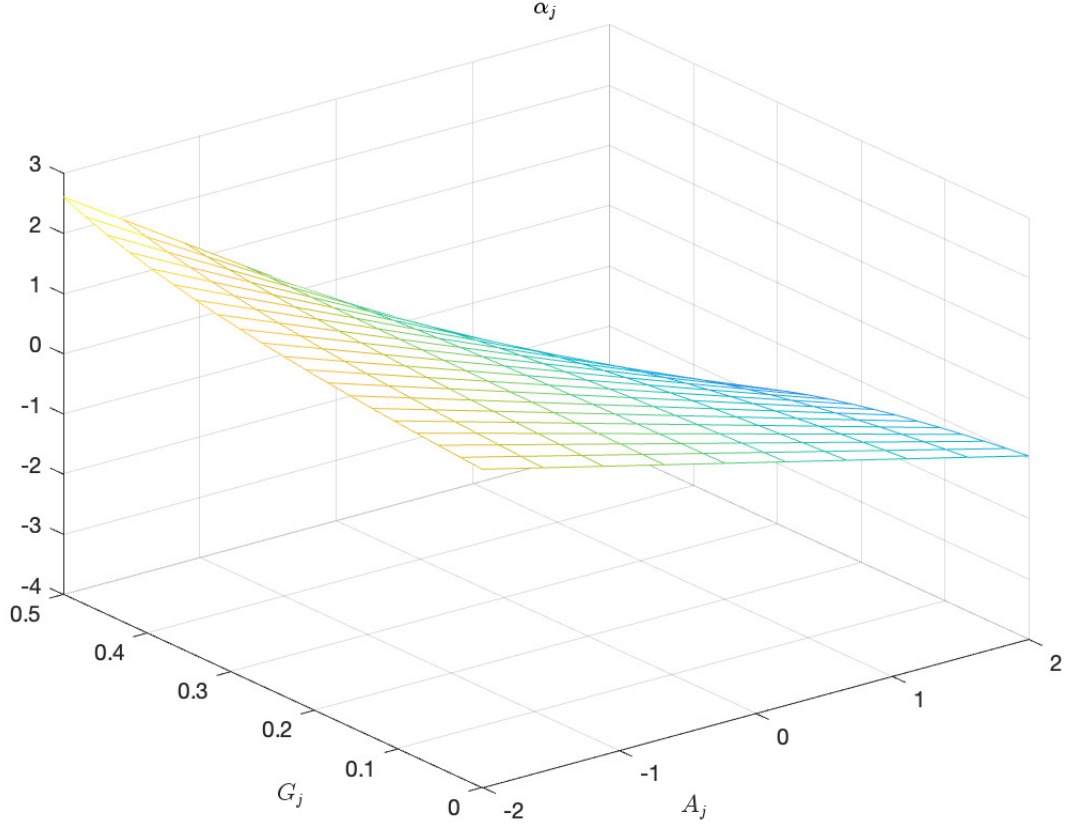


Table IA.1: Gambling propensity and the post-profitability-announcement drift: Portfolio analysis

For each stock in month t , we use the quarterly report announced in the past three months to compute the gross margins (*Profitability*). GP equals 1 if in the past six months, the average stock price (PRC) is in the bottom three deciles and the idiosyncratic volatility ($IVOL$) and skewness ($ISKEW$) are both in the top three deciles in the cross-section, and 0 otherwise. In the month, we divide the sample stocks into two equal groups based on *Profitability*, and independently into two groups based on GP ; this leads to 2×2 portfolios. We compute the return of each portfolio by weighting stocks in the portfolio equally. This table presents the excess return over the risk-free interest rate (Exret), and benchmark-adjusted returns based on the CAPM, the Fama and French (1993) and Carhart (1997) 4-factor model (FFC4), and the Fama and French (2015) 5-factor model (FF5) for each portfolio, as well as each high-*Profitability* minus low-*Profitability* (conditional on GP) portfolio, and the return difference between high-*Profitability* minus low-*Profitability* portfolios conditional on $GP = 1$ and $GP = 0$. We correct standard errors using the Newey-West method with up to three lags. t -statistics are reported in parentheses. *, ** and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 1977 to December 2024. See Appendix B for variable definitions.

<i>Risk-adjusted return</i> $\times 100$									
	Exret			CAPM		FFC4		FF5	
	All	$GP = 0$	$GP = 1$	$GP = 0$	$GP = 1$	$GP = 0$	$GP = 1$	$GP = 0$	$GP = 1$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Low <i>Profitability</i>	0.604*** (2.47)	0.651*** (2.78)	-0.066 (-0.17)	-0.122 (-1.07)	-1.051*** (-3.56)	-0.114** (-2.11)	-0.871*** (-4)	-0.172*** (-3)	-0.722*** (-3.39)
(2) High <i>Profitability</i>	1.156*** (4.81)	1.129*** (4.81)	1.281*** (3.69)	0.348*** (2.97)	0.389 (1.36)	0.365*** (5.96)	0.455** (2.31)	0.254*** (4.53)	0.57*** (2.91)
(2)-(1)	0.553*** (8.75)	0.479*** (7.69)	1.347*** (8.22)	0.47*** (7.01)	1.44*** (8.77)	0.479*** (7.91)	1.326*** (8.13)	0.425*** (7.73)	1.292*** (7.88)
Difference			0.868*** (5.41)		0.97*** (6.11)		0.847*** (5.4)		0.867*** (5.52)

Table IA.2: Gambling propensity, advertising, and risk-adjusted returns: Portfolio analysis

For month t in the period from July of a year to June of the next year, we use the annual report in the past fiscal year to compute ADV , the industry-adjusted growth of the advertising expense. GP equals 1 if in the past six months, the average stock price (PRC) is in the bottom three deciles and the idiosyncratic volatility ($IVOL$) and skewness ($ISKEW$) are both in the top three deciles in the cross-section, and 0 otherwise. In the month, we divide the sample stocks into two equal groups based on ADV , and independently into two groups based on GP ; this leads to 2×2 portfolios. We compute the return of each portfolio by weighting stocks in the portfolio equally. This table presents the excess return over the risk-free interest rate (Exret), and benchmark-adjusted returns based on the CAPM, the Fama and French (1993) and Carhart (1997) 4-factor model (FFC4), and the Fama and French (2015) 5-factor model (FF5) for each portfolio, as well as each high- ADV minus low- ADV (conditional on GP) portfolio, and the return difference between high- ADV minus low- ADV portfolios conditional on $GP = 1$ and $GP = 0$. We correct standard errors using the Newey-West method with up to three lags. t -statistics are reported in parentheses. *, ** and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample period is from January 1977 to December 2024. See Appendix B for variable definitions.

<i>Risk-adjusted return $\times 100$</i>									
	Exret			CAPM		FFC4		FF5	
	All	$GP = 0$	$GP = 1$	$GP = 0$	$GP = 1$	$GP = 0$	$GP = 1$	$GP = 0$	$GP = 1$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Low ADV	0.958*** (4.3)	0.958*** (4.44)	0.861** (2.21)	0.272** (2.02)	-0.022 (-0.07)	0.193** (2.43)	0.119 (0.48)	0.043 (0.55)	0.152 (0.63)
(2) High ADV	0.799*** (3.41)	0.864*** (3.77)	-0.072 (-0.2)	0.113 (0.89)	-0.999*** (-3.56)	0.098 (1.35)	-0.817*** (-3.65)	-0.028 (-0.36)	-0.752*** (-3.49)
(2)-(1)	-0.159*** (-3.18)	-0.094* (-1.98)	-0.933*** (-4.06)	-0.159*** (-3.18)	-0.976*** (-4.18)	-0.095** (-2.22)	-0.936*** (-4.32)	-0.072* (-1.65)	-0.903*** (-3.97)
Difference			-0.839*** (-3.65)		-0.818*** (-3.42)		-0.841*** (-3.8)		-0.832*** (-3.61)