Investor Attention, Social Interaction, and the Salience Effect.

Abstract

Motivated by existing evidence of the salience theory (ST) effect, we examine the roles of investor attention and social interaction in the negative relationship between salience theory values and future returns. We find that the salience effect is stronger and concentrates more in stocks with low investor attention (proxied by low analyst coverage and salient earnings surprises) but weakens in stocks with higher investor attention. We also demonstrate that the salience effect is more pronounced in stocks with high retail ownership. Additionally, intense social interaction (proxied by Facebook social connectedness or population density of the county where a firm's headquarters is located) further strengthens the salience effect. Our findings offer new insights into how investor attention and social interaction drive and contribute to the salience effect.

1. Introduction

The salience theory, a significant concept in understanding investor behavior, posits that due to cognitive limitations, investors tend to focus more on the salient payoffs of stocks. This leads them to evaluate a stock by comparing its payoff with all available market stocks (Bordalo et al., 2012). The theory captures the distortion in return expectations caused by salient thinking, emphasizing that stocks with the most salient payoffs stand out relative to the payoffs of other stocks in the market. The salience-based asset pricing of Bordalo, Gennaioli, and Shleifer (2013a) argues that retail investors, being more attracted to stocks with high salient upsides, create excess demand for these stocks, leading to overvaluation and lower future returns. Conversely, stocks with salient downsides become undervalued and earn higher subsequent returns. This asset anomaly is known as the salience theory effect (ST effect).

Building on the salience theory, several empirical studies have emerged to provide robust evidence and explain the salience effect. Cosemans and Frehen (2021) define the salience theory (ST) as the distortion in return expectations caused by salient thinking, showing that it significantly predicts a negative relationship in the cross-section of US stocks' future returns. Cakici and Zaremba (2022) document compelling evidence of the negative relationship between the salience theory value and future returns in the international market, explaining that the salience effect is dominated by microcaps and periods of extreme market conditions. Bordalo, Gennaioli, and Shleifer (2022) highlight salience theory as a subset of a stimulus that drags attention bottom-up due to its contrast, surprise, and prominence, leading to over or underweighting goals. However, an important aspect yet to be explored in this model is how investors with limited attention become aware of whether a stock return is highly salient. Moreover, social interaction could be a strong influence, as it can induce investor attraction and excess demand for stocks with high salient payoffs, even when investors do not possess an intrinsic preference for skewness (Han, Hirshleifer, and Walden, 2021). While previous studies focus on understanding the salience effect and its relation in the cross-sections of returns, how investor attention and the geographical structure of social connectedness drive investors' attraction to ST stocks remains unexplored.

Several behavioral finance studies indicate that investor attention plays a vital role in shaping trading behavior, as heightened attention toward certain stocks or market trends can amplify trading activities and price pressures. For example, limited investor attention to publicly available information can trigger market overreactions and price changes positively and negatively (Barber and Odean, 2008; Cohen and Frazzini, 2008). In addition, social interaction, facilitated by various communication channels such as word of mouth and social media platforms, can significantly influence investor attention and the salience of specific information (Bali et al., (2021). Therefore, we argue that social interaction influences investors' attraction and strengthens the negative relation between salience and future stock returns. When investors engage in social interaction, they are exposed to diverse information and opinions, which can shape their perceptions and investment decisions. Salient information can spread rapidly through social channels, capturing the attention of a broader audience and potentially amplifying market trends. For example, Han, Hirshliefer, and Walden (2021) find that investors' attraction to stocks with high volatility and skewness is shown to increase with the intensity of social interactions when high returns are disproportionately communicated through word of mouth and extremely positive returns are highly salient. In this case, we expect retail investors' attraction to ST stocks in socially connected regions to be driven by their increased awareness derived from high attention and social interactions of the salience effect.

Therefore, we investigate whether investor attention drives excessive attraction to ST stocks and whether social interaction significantly drives investor attraction and strengthens the salience effect. Since retail investors are subject to limited attention and strongly influenced by intense social interactions, we predict that salience will be more pronounced in stocks with high retail ownership.

We contribute to the literature as follows. First, we add to the rapidly growing studies on the impact of salience effect on individual decision-making by complementing the studies on the impact of salience theory on stock returns (Cosemans and Frehen 2021; Cakici and Zaremba (2022); Liu et al. 2023), individual risk decisions (Bordalo et al., 2012), judicial decisions (Bordalo et al., 2015) and tax effects (Chetty et al., 2009).

Second, we add to the general literature on the influence of investor behavior in understanding and explaining anomalies in the stock markets. Prior literature demonstrates how cognitive limitation, herding behavior, and sentiment significantly affect investor decisions and market outcomes. Our research provides distinct contributions to the significant roles played by limited investor attention (e.g., Barber and Odean, 2008; Barberis, 2013), amplified by social interaction (Hirshleifer et al., 2009; Bali et al., 2021) in explaining market return anomalies such as the salience effect.

Lastly, we contribute to the growing literature on the impact of social networks in the securities market. Social interaction assists in spreading valuable information (Bailey et al. 2018b) and amplifies behavioral biases through disproportionate reporting of payoffs (Han et al. 2021; Hirshleifer, 2020)

The rest of this paper is structured as follows: Section 2 reviews the extant literature and hypothesis development for this study. Section 3 highlights the data sources used in the study and details the construction of key variables. Section 4 reports the results from the empirical analysis and robustness tests. Section 5 concludes the paper.

2. Literature Review

2.1 Salience Effect

Naturally, unusual attributes are more susceptible to catching the attention of individuals when faced with decision-making and choices. Salience refers to "the tendency whereby one's attention is distinctly concentrated on a specific area of the environment rather than on others, which causes the information contained in that area to receive disproportionate weighting in subsequent judgments" (Taylor and Thompson (1982). A novel approach in decision theory by Bordalo et al. (2012) proposed the salience theory of choice under risk, arguing that investors evaluate a stock in the context of all available stocks in the market. The investors' attention is drawn to the most salient payoffs of the available stocks. Therefore, the stock's most salient payoffs are those that stand out relative to the market average payoffs, and these salient returns are allocated the largest weight. The salience theory has also been widely explored and applied across diverse fields to explain consumer choices (Bordalo et al., 2013), individual behavioral responses to taxation (Chetty et al., 2009), and judicial decisions (Bordalo et al., 2015). Furthermore, Dessaint and Matray (2017) find that corporate managers re-estimate and overweight their risk probabilities when they see a disaster is temporarily salient. Recently, Cosemans and Frehen (2021) presented empirical evidence of the salience-based asset pricing model in the US stock market and documented a negative relationship between a stock's salient theory value and future returns. They suggest that because investors are more attracted to stocks with salient upsides, it could lead to excessive demand, which induces mispricing, market overreactions, and lower earnings of future returns. Since retail investors are prone to attentional biases, we expect salience theory value to be more pronounced in stocks with low investor attention.

Following Bordalo et al. (2012,2013a) and Cosemans et al. (2021) prediction of the salience theory model, several studies have tested evidence of the salience effect in environments outside the US. Cakici and Zaremba (2021), exploring the effects of a salience-based asset pricing model using 49 international stock markets data from 1990 to 2020, find that high ST stocks have low returns in most individual countries and pooled international market samples. However, their report indicates that the salience effect is solely observed and priced among small-sized stocks (representing 3% of the global market capitalization). In addition, Cakici and Zaremba (2021) argue that the salience effect is more evident during extreme market conditions and is substantially associated with the short-term return reversal effect. Using the Chinese stock market data, Liu, Sun, and Zhu (2021) also document a negative relation between the salience theory value and future returns. The study finds that short-sale constraints and investors' strong lottery preferences could drive the salience effect.

Exploring the cryptocurrency market, Cai and Zhao (2022) show empirical support for the predictive power of salience-based asset pricing in the cross-section of crypto market returns. More broadly, Chen et al. (2022), using 1738 cryptocurrency data samples, demonstrate evidence of a relatively stable salience effect in the time series analysis and cross-section of cryptocurrency returns. Consistent with the views of Cakici and Zaremba (2021), they find that the salience effect is mainly domiciled in microcaps, which constitute just 3% of the total cryptocurrency market capitalization. Furthermore, supporting evidence is demonstrated in the corporate bond market (Lin and Zhang, 2022) and the options market (So and Zhang, 2024). Using a natural experiment and individual investors trading data from a Chinese brokerage, Frydman and Wang (2020) demonstrate that manipulating the salience of a stock's capital gain information on the investors' screen influences trading behavior leading to a more substantial disposition effect.

2.2 Investors' attention and stock returns

Consistent with a growing body of empirical literature on behavioral finance, several studies have examined the influencing roles of investor attention in the security markets. For example, earlier research extensively finds that investors' attention constraints to publicly available information could give rise to underreactions to important news in the market (Peng and Xiong, 2006; Cohen and Frazzini (2008); Hirshleifer et al., 2009). Other studies argue that high investor attention can trigger investor overreaction to relevant valuable information in the market (Barber and Odean, 2008; Gilbert et al., 2012; Kaniel et al., 2017). Consistent with this view, Nguyen and Pham (2021) examined 11 well-documented stock market anomalies and found 9 of these anomaly effects are more pronounced during high attention than low attention moments. Similarly, Bali et al. (2021) also show that the excessive attraction of individual investors to lottery stocks is strongly driven by high investor attention and intense social interaction. Conversely, Hur and Singh (2021), while exploring the role of investor attention in the idiosyncratic volatility (IVOL) puzzle, find that the negative IVOL effect is dominated among stocks with the lowest investor attention. Following this mechanism, we argue that the salience effect is significantly

stronger in stocks with low investor attention.

2.3 Social interaction and stock returns

Social interaction has also been strongly associated with being one of the critical factors driving investor attraction and active participation in the stock market. For example, Hong et al. (2004) utilized church attendance and conversation with neighbors' data to show that social interaction positively relates to stock market participation in the US stock market. Similarly, Brown et al. (2008), examining the effects of communication (word of mouth) on stock market participation, indicate a relationship exists between the average engagement of an investor's community in stock trading activities and the investor's decisions to buy and hold stocks.

Employing the novel Facebook social connectedness index (SCI) of Bailey et al. (2018b), a growing body of empirical studies is emerging to show the vital role of social interactions in influencing the economic decisions of individuals and firms. Recently, Bailey et al. (2021) found that social connectedness significantly impacts trade flows between domestic and international regions. In a related study, Kutcher et al. (2022) show that institutional investors tend to invest more in firms located in areas with more social connections. Han, Hirshleifer, and Wang (2021) find that social interaction greatly influences investors to pay more attention to lottery stocks, even if such investors do not have a preference for positive skewness. Exploring a firm-level empirical analysis, Bali et al. (2021) used the Facebook SCI and population density as measures of social interactions. They find that the intensity of social interaction stimulates increased investor awareness and attraction to lottery stocks.

Furthermore, more studies are emerging to provide empirical evidence supporting the critical role of social interactions in the credit market. Nguyen et al. (2023) find that venture capital invests more in portfolio companies with more socially connected regions. Rehbein and Rother (2020) show a positively significant relationship between social proximity and bank lending activities between US counties. Building on the extant literature, we explore the role of social interaction in driving investors' attraction to salient stocks.

2.4 Research Hypothesis Development

Several behavioral finance studies indicate that investor attention plays a vital role in shaping trading behavior. High investor attention toward certain stocks or market trends can amplify trading activities and price pressures. For example, limited investor attention to publicly available information can trigger market overreactions and price changes positively and negatively (Barber and Odean, 2008; Cohen and Frazzini, 2008). Several documented studies show how retail investors' behavior is influenced by both cognitive biases and the availability of information. Kumar 2009 and Bali et al. (2011) demonstrate that regardless of retail investors' preference for positive skewness, they tend to choose stocks based solely on the stock characteristics they know and pay attention to. Similarly, the salience theory suggests that investors tend to overweight information that stands out, potentially leading to mispricing in the stock market. In the model proposed by BGS (2012, 2013), all investors are assumed to be salient thinkers, meaning they are prone to focusing on more noticeable information, such as recent gains or losses, mainly when they have limited attention or cognitive resources. In their empirical study, Cosemans and Frehen (2021) explained that visibility is crucial in the initial decision-making phase, determining which stocks capture investor attention and are considered for investment choices. In the subsequent phase, salience shapes the selection process by drawing attention to specific returns, influencing investors' expectations of future stock performance.

Consistent with these insights, it becomes evident that the level of investors' awareness of certain stocks may impact the strength of the salience effect. Specifically, we expect the negative relationship between salience theory value and future stock returns to be dominant in stocks with lower investor attention. Therefore, we test the following hypothesis:

Hypothesis 1: The salience theory value is more robust (weaker) in stocks with low (high) investor attention.

Since extant empirical studies (such as Han and Kumar, 2013; Lin and Liu, 2018; Nagel et al., 2005) show that retail ownership can hinder arbitrage by decreasing the availability of stocks lendable in the short-selling market due to their unsophisticated nature, limited attention and preference for skewness, we posit that the salience effect will be more amplified in stocks dominated by high retail ownership. For example, Bali et al. 2021 demonstrate that the lottery anomaly becomes more pronounced when retail investors own more lottery stocks as they focus more on the salient features of lottery stocks, mostly small-sized, highly volatile stocks. Similarly, Coseman and Frehen (2021) and Cakici and Zaremba (2021) find that the salience effect is stronger among small and illiquid stocks with greater limits to arbitrage. Therefore, we expect the salience effect to be more pronounced for highly retail-owned stocks. We test the following hypothesis:

Hypothesis 2: The salience theory value is more pronounced in stocks heavily held by retail investors.

Based on the existing rationale, we also posit that social interactions could drive retail investors' attraction to salient stocks. For example, Han, Hirshleifer, and Walden (2021) argue that investors are likely drawn to volatile and positively skewed stocks due to the intensity of social interactions when extreme returns are salient and disproportionately reported. Leveraging this study, Bali et al. (2021) further explained that intense social interactions can boost retail investors' awareness of extreme returns through word-of-mouth communication. Therefore, we also conjecture that since retail investors are engaged in salient thinking and subject to limited attention, we expect that the intensity of social interaction drives the attraction to salient stocks and enhances the salience effect. Therefore, we test the following hypothesis:

Hypothesis 3: Social interaction strengthens the negative relationship between salience theory value and future stock returns.

3. Data and Variable Definitions

3.1 Data Collection

For the sample period from January 1980 to December 2022, we downloaded all common stock data traded on the NYSE, AMEX, and NASDAQ exchanges from the Center for Research in Security Prices (CRSP) database. We collect the accounting variables such as earnings per share (EPS) and book value from the Compustat database, analyst coverage data from the Institutional

Brokers' Estimate System (I/B/E/S) database, and the institutional ownership data from Thompson 13F filings for 1980 to 2022. The Fama and French (2015) five factors, including the market returns (MKT), size (SMB), book-to-market (HML), momentum (UMD), profitability (RMW), and investment (CMA), are obtained from Kenneth French's data library. The liquidity factor (PS) is obtained from Lubos Pastor's data library. Stocks are removed from the analysis if the closing price is less than $5 per share or more than $1000 at the end of the previous month to reduce structure effects. Stocks are included in the study for a given month if a minimum of 15 daily return observations is available to calculate salience theory value and if the historical data are also available to compute the different firm characteristics employed as control variables. We winsorize our data between 1% and 99% to guarantee that outliers do not impact our report results from the empirical analysis.

3.2 Key Variables

3.2.1 Salience Theory (ST)

The salience theory premise is that investors' attention is associated with the salience of payoffs. Specifically, investors are more likely to overweight prior high-salient returns and underweight the non-salient ones. Another crucial implication of salience theory is that investors make trading decisions within context. Bordalo, Gennaioli, and Shleifer (2012; 2013a) constructed a model that merges context-specific choices and endogenous asset allocation concepts to depict how salience theory affects decision-making in financial markets.

Following Cosemans and Frehen (2021), we also assume that investors' choice set consists of all stocks available in the market. We construct the salience theory value using three basic steps.

Firstly, we define the salience (σ_{is}) of a stock's return on day s (r_{is}) is subject to its distance from the average market payoff on that day ($\overline{r}_s$), as follows:

The salience theory assumes that investors evaluate a stock in the context of all available stocks in the market, i.e., the investors' attention is directed to the most salient returns of the stocks available for choice. Therefore, the stock's most salient returns stand out relative to the returns of other stocks, and these salient returns are assigned the largest weight. Salience theory value is calculated as the covariance of the decision weights (ω_{is}) and the stock returns (r_{is}) over the estimation period. The main prediction of the salience-based asset-pricing model is a negative relationship between the salience theory value and expected future returns (Cosemans and Frehen, 2021).

The salience theory value is determined following the basic steps:

a) We calculate the salience of each stock's daily payoff within the measurement period.

$$\sigma(r_{is}, \overline{r}_s) = \frac{|r_{is} - \overline{r}_s|}{|r_{is}| + |\overline{r}_s| + \theta} \tag{1}$$

where the salience $\sigma(r_{is}, \overline{r}_s)$ of a stock's daily return on day s (r_{is}) depends on its distance from the average return in the market on that day ($\overline{r}_s$). Following Bordalo et al. (2012) and Cosemans and Frehen (2021), we also apply a baseline value of **θ=0.1** ($\theta > 0$ to avoid the case that zero-return payoffs always get the most salience regardless of the market index returns).

b) To calculate the salience weight for stock i on day s within, we rank the daily returns in each month in descending order of salience and apply the rank (k_{is}) in the following equation.

$$\omega_{is} = \frac{\delta^{k_{is}}}{\sum_{s'} \delta^{k_{is'}} * \pi_{s'}}, \qquad \delta \in (0,1), \tag{2}$$

Where and **δ=0.7** (a parameter used to describe the impact of salience on decision weights). When δ = 1, there are no salience distortions, and decision weights are equal to objective probabilities (ω_{is} = 1 for all s ∈ S). This case corresponds to the rational decision maker. When δ < 1, the decision maker is a salient thinker who overweight salient states (ω_{is} > 1) and underweights non-salient states (ω_{is} < 1). When δ → 0, the salient thinker considers only a stock's most salient payoff and neglects all other payoffs. k_{is} is the rank of salience payoff; r_{is} ranging from 1 (most salient) to S (least salient), and π = 1/S as the scaling factor. S denotes the set of states and, in this case, the number of trading days within the ranking period.

c) Lastly, we calculate the monthly salience theory value for stock i as the covariance between the stock's salience weights and daily returns within month t:

$$ST_i = cov(\omega_{is}, r_{is}). \tag{3}$$

As highlighted by Cosemans and Frehen (2021) in the salience-based asset pricing model, if the salience theory value is greater than zero, i.e., investors tend to put larger weights on extremely positive stock's payoffs, the stock will be overvalued, leading to higher current prices and lower subsequent returns. Conversely, if the salience theory value is less than zero, i.e., investors tend to put large weights on extremely negative stock payoffs, then the stock will be undervalued, resulting in low current prices and subsequent high returns. Hence, the salience-based asset-pricing theory predicts a negative relationship between the ST and future stock returns.

3.2.2 Proxies for Investor Attention

The other main variables used in this study are the investor attention proxies (ATTN). We investigate whether investor attention is associated with the salience effect. The challenge in conducting this test is obtaining measures of attention during the decision-making process. Following Bali et al. (2021), we capture various areas of investors' attention using two proxies.

Firstly, we adopt analyst coverage (CVRG) to measure the firm's prominence in public conversations via financial media and the web. Analysts' coverage draws more attention to firms as investors closely monitor analyst forecasts and recommendations (Barber et al., 2001). Analyst coverage is measured as the number of distinct earnings forecasts for stocks in the portfolio formation over the past year. We assume that stocks with high salient payoffs get noticed by the public, and such news tends to spread quickly to the reach of investors who swiftly analyze these stocks.

Secondly, following Hirshlieifer et al. (2001) and Barber and Odean (2008) findings that firms in the news with both positive and negative earnings surprise likely attract investor attention, we also use the absolute value of stock's unexpected earnings (|SUE|) to calculate the saliency of company's news releases. Following Bernard and Thomas (1989, 1990) and Bali et al. (2021), we define SUE as quarterly earnings surprises computed as the difference between the latest quarterly earnings per share (EPS) after excluding extraordinary items and the EPS four quarters ago, divided by the standard deviation of quarterly earnings surprises over the past eight quarters.

Additionally, we measure retail ownership (RHLD) as one minus the fraction of shares outstanding held by institutional investors, available from the Thomson Reuters Institutional Holdings (13F) database from 1980 to 2022. We aggregate a stock's quarterly institutional ownership scaled by its total shares outstanding at the 8-character CUSIP level. We then merge the quarterly retail ownership variable with the CRSP data by CUSIP.

3.2.3 Proxies for Social Interactions

The last two proxies used in this study are social interaction proxies (SOCIAL). We follow the studies of Bali et al. (2021) and use the population density (PD) and the Facebook Social Connectedness Index (SCIH) of the county in which the company's headquarters is situated to proxy for social interactions. Owing to the home bias phenomenon, which relates to investors' perceived preference for stocks from local firms, investors tend to discuss their earnings from trading local stocks, leading to increased awareness and more demand for such stocks (Hong et al., 2008).

Firstly, we utilize the Facebook social connectedness index (SCI) developed by Bailey et al. (2018b) as a proxy for social interactions. Leveraging on the vast and representative nature of Facebook's user base, the SCI index captures the investor social ties between US counties based on Facebook friendships as of April 2016. The use of this proxy is motivated by the studies that show that lottery anomaly becomes more amplified for stocks located in counties with more intense social interactions (Bali et al. 2021, Han, Hirshleifer, and Walden 2021 and Kutcher et al. 2022). Facebook, the world's largest online social networking service with more than 2.1 billion active users, primarily facilitates interactions among real-world friends, making its networks more reflective of actual social connections than other platforms like Twitter. The survey of Facebook users in the United States by Duggan et al. (2016) indicates that Facebook usage rates among U.S.-based online adults were relatively constant across various demographics, such as income, education, race, and residential settlements.

We measure the social connectedness for each headquarters county (SCIH) as the aggregated SCI of the headquarters county with all other counties in the United States. We assign the county-level SCIH to a firm based on its headquarters location and link the firm-level SCIH to stock information.

$$Social\ Connectednes\ index_{i,j} = \frac{FB\_Connections_{i,j}}{FB\_Users_i * FB\_Users_j}$$

Where, FB_Users_i and FB_Users_j are the number of Facebook users in locations i and j, and $FB\_Connections_{i,j}$ is the total number of Facebook friendship connections between individuals in the two location or counties.

We define $SCIH_i$ as the total connectedness of county i with all counties in the United States:

$$SCIH_i = \sum_{j=1}^{i} SCI_{i,j}$$

Population Density (County-level): The use of population density (PD) measures is motivated by the finding that the more populated a city is, the greater its social connections and interactions (Bailey et al., 2018b). Therefore, it is assumed that investors from areas with a larger population have a greater tendency to discuss with friends the profits earned from local stock investments, especially those that exhibit salient features. The county-level population density (PD) is from the 1980, 1990, 2000, and 2010 U.S. Census. The decennial PD is linked to a firm's headquarters based on the Federal Information Processing Standards (FIPS), which uses a five-digit coding system with the first two digits designating the state and the last three digits designating the county.

4. Empirical Results

4.1 Summary Statistics and Characteristics Analysis

Table 1 reports the time-series averages of the cross-sectional summary statistics and the correlation matrix of the stock characteristics. In Panel A, we show that, on average, a stock in our data sample has a salience theory value of 0.0045, covered by around 4 analysts, and has a |SUE| of 0.998. The SCIH exhibits a mean score of 2.19, with an average headquarters population density of 4,844 people per square mile, consistent with the existing literature (Bali et al., 2021) of 4,890 people per square mile. The mean of stock returns is 0.0149 per month and has an RHLD mean value of 48, indicating the percentage of shares held by retail investors, which is lower than the RHLD of 57 reported by Bali et al. (2021).

Table 1 Panel B reports the cross-sectional correlations between the variables used in this study. The table indicates that salience theory value is strongly and positively correlated with MAX (0.59) and IVOL (0.29) and negatively correlated with CVRG, |SUE|, SCIH, SIZE, REV, and PRICE, indicating that stocks with high salience theory values are small stocks, have lower attention, and low priced. Table 1 Panel B also shows CVRG has a strong positive correlation with SIZE (0.52) and a negative correlation of -0.31 with RHLD, indicating we tend to have higher analyst coverage for larger firms and less coverage for stocks with high retail ownership (RHLD).

[Table 1]

Table 2 presents the average characteristics of portfolios sorted based on the ST value. The table shows that stocks with higher ST values are small and have lower analyst coverage (CVRG) and lower earnings surprise (|SUE|) when compared with low ST stocks. The high ST portfolios tend to have higher maximum daily return (MAX), higher idiosyncratic volatility (IVOL), higher BM, higher market beta (BETA), and more illiquid (ILLIQ), consistent with the correlation coefficients shown in Panel B of Table 1.

[Table 2]

4.2 The Salience Effect

The salience theory of Bordalo et al. (2012) explains that investors are primarily drawn to the most salient and unusual features when making investment decisions due to cognitive limitations. Consequently, Cosemans and Frehen (2021) posit that salient thinkers would overweight salient upsides (downsides), leading to overvaluation (undervaluation) of the stock and generating low (high) subsequent returns. Following this mechanism, we first re-examine the relation between the salience effect of Cosemans and Frehen (2021) and various firm characteristics in a different sample period using the univariate, bivariate, and multivariate tests.

4.2.1 Univariate Portfolio Sorting

Table 3 reports the equal-weighted (EW) and value-weighted (VW) average monthly excess returns of stocks sorted into deciles based on ST values at the end of each month from January 1980 to December 2022. Portfolio 1 (10) consists of stocks with the lowest (highest) ST value in the previous month. Each portfolio's equal-weighted (EW) and value-weighted (VW) average returns are calculated over the following month. We present the time-series average of the excess portfolio returns, FF-3 alpha, Cahart (1997) four-factor alpha, FF-5 alphas, and a seven-factor alpha obtained from the FF-Cahart model augmented with PS liquidity factor reported with the Newey and West (1987) t-statistics in parenthesis. Lastly, we construct a zero-investment portfolio that buys the highest decile and shorts sell the lowest decile. Table 3 demonstrates a strong and robust salience effect in the US stock market, consistent with the findings of Cosemans and Frehen (2021). On average, the high minus low ST portfolio generates a monthly equal-weighted excess return of -0.70% per month with a t-statistic of -5.20 and a value-weighted excess return of -0.63% per month with a t-statistic of -4.51, consistent with the -0.60% (t-statistics =-4.80) reported in Cosemans and Frehens (2021). Furthermore, the alpha spreads generated from the FF-3 (-0.72%, t-stat=-5.01), Cahart 4 factor (-0.74%, t-stats=-4.96), FF-5 (-0.78%, t-stats=-5.22) and 7 factor (-0.79%, t-stats=-5.26) demonstrates that the alpha spreads remain strong and statistically significant. Our results confirm the extant evidence of a lower return for stocks with salient upsides similar to Cosemans and Frehens (2021) in the US stock market and Cakici and Zaremba (2022) findings in the global market. Additionally, we observe a spontaneous return drop in portfolios 9 and 10, which suggests that the salience effect is dominant in the highest ST portfolio, suggesting the speculative behavior of retail investors in the stock market.

[Table 3]

4.2.2 Firm-Level Fama-Macbeth Regressions

To further re-examine whether our result survived after jointly controlling for well-known documented stock return predictors, we use the following model to run the Fama-MacBeth cross-sectional regressions:

$$ExR_{i,t+1} = \lambda_{0,t} + \lambda_{1,t}\mathrm{ST}_{i,t} + \lambda_{2,t}\mathrm{X}_{i,t} + \varepsilon_{i,t+1} \tag{6}$$

where $ExR_{i,t+1}$ is the excess return on stock i in month t+1, $\mathrm{ST}_{i,t}$ denotes proxy for salience theory value of stock i in month t, and $\mathrm{X}_{i,t}$ is a vector of control variables including the market beta (β MKT), firm size (SIZE), book-to-market ratio (BM), momentum (MOM), illiquidity (ILLIQ), maximum daily return (MAX), idiosyncratic volatility (IVOL), short-term reversal (REV), log of price (PRICE) and asset growth (AG).

The result of the univariate regressions with ST reported in Table 4 column (1) shows a slope coefficient of -9.0693 with a t-statistic of -3.93, affirming a significantly negative relation between ST and subsequent stock returns. The results of the bivariate regressions with ST presented from columns (2) to (11) show that the salience theory value survives and remains strong after controlling for the individual variables. In the last column, we report the average slope coefficient of -7.6533 with a t-statistics of -4.42 in the multivariate regression, controlling for other variables simultaneously. Therefore, our results confirm the existence of a robust negative relation between salience theory value and future stock returns.

[Table 4]

4.3 Investor Attention and the Salience Effect

We investigate the relationship between investor attention and salience effect, considering that the two theories are based on cognitive bias. Cosemans and Frehen (2021) posit that salience and attention can impact trading decisions and stock prices. Visibility is crucial in the initial phase of the decision-making process because it dictates which stocks capture investors' attention and make it into the consideration set. In the subsequent phase, salience influences the selection among these stocks by highlighting which returns catch investor attention, shaping their expectations of future stock returns. We next examine whether investor attention influences the negative relationship between salience theory value and future returns. We expect the salience effect to be more pronounced in stocks with low investor attention and hypothesize that high investor attention mitigates the salience effect in the stock market.

Table 5 reports the FF5 alphas for the EW and VW portfolios sorted by ST value and each of the two attention proxies. The difference in the returns between the high-ST and low-ST deciles within each attention-based group is reported in the last row of the table. Panel A shows that the ST portfolio returns are very high among stocks with low CVRG but insignificant in stocks with high CVRG group. For the EW portfolios, the FF5 alpha spread in the low CVRG group is -1.01% per month with a t-statistic of -6.26, while the FF5 alpha spread in the high CVRG group is insignificant at -0.69% per month with t-statistic of -1.30. For the VW portfolio, the FF5 spread in the low CVRG group is significant at -0.94% (t-stats=-5.71) and insignificant in the high CVRG group at -0.22% (t-stats=-1.16). The results support our hypothesis that the salience effect is more pronounced in stocks with low investor attention.

Panel B reports the second attention proxy based on the latest earnings surprise |SUE|. Panel B shows that the salience effect is more pronounced in the low and medium |SUE| group but smaller in the high |SUE| group. For EW portfolios, the FF5 alpha spread in the low and medium |SUE| groups are similar and larger at -0.90% per month (t-stats=-5.52) and -0.99% (t-stats=-6.51), whereas the FF5 alpha spread for stocks in the high |SUE| group is also significant but smaller, -0.50% per month (t-stats=-2.68). Our result indicates that the salience theory value is stronger when investors' attention to stocks is low. As documented by Cakici and Zaremba (2021), the salience effect is majorly dominated among microcaps, which justifies reasons for such firms to attract low analyst coverage, as presented in our findings. Our results demonstrate that the salience effect is more prominent for stocks that receive lesser investor attention based on low analyst coverage and surprise earnings announcements.

[Table 5]

To examine the impact of investor attention on the salience effect while simultaneously controlling for other well-known predictors of future returns, we next test the hypothesis by interacting the two attention proxies (CVRG and |SUE|) with ST value at the firm level using the Fama and Macbeth (1973) regressions. We conduct monthly cross-sectional regressions based on the following model specifications:

$$ExR_{i,t+1} = \lambda_{0,t} + \lambda_{1,t}\mathrm{ST}_{i,t} + \lambda_{2,t}(\mathrm{ST}_{i,t} \times \mathrm{ATTN}_{i,t}) + \lambda_{3,t}\mathrm{X}_{i,t} + \varepsilon_{i,t+1} \quad (7)$$

where $ExR_{i,t+1}$ is the excess return on stock i in month t+1, $\mathrm{ST}_{i,t}$ denotes proxy for salience theory value of stock i in month t, $\mathrm{ATTN}_{i,t}$ denotes proxy for investor attention to stock i in month t and $\mathrm{X}_{i,t}$ is a vector of control variables.

Table 6 presents the Fama-Macbeth regression results, including the interaction terms between each investor attention proxy and ST. We find that the interaction variables in specifications (1) and (2) are positive and statistically significant, indicating that high investor attention gradually weakens the salience effect, and the effect is strongest for stocks in the low attention groups. Columns 1 and 2 show that the interaction term between ST value and each of the attention proxies (CVRG and |SUE|) has an estimated coefficient of 0.0188 (t-stat=2.02) and 0.0263 (t-stat=2.98), respectively. Furthermore, we find that coefficient estimates for the control variables included in the regression are generally consistent with the findings of extant literature. For example, SIZE and REV are negatively significant, as Fama and French (1992) and Jegadeesh and Titman (1993) reported. Our regression results correspond with our portfolio results, indicating that the negative salience and future returns relationship is stronger for stocks that attract lower investor attention.

[Table 6]

Next, we partitioned our sample period into three groups based on tercile low, medium, and high investor attention breakpoints. Then, we conduct monthly Fama-Macbeth regressions as in model 6. Table 7 reports the estimated coefficients of the Fama-Macbeth regressions of the monthly expected stock returns on ST values and other control variables under different attention levels. Consistent with the bivariate portfolio sorts, we find the coefficient of ST value in the high attention is smaller and weakly significant, as reported in column 3, where the high CVRG group has =0.0483 (t-stats=-1.78) and high |SUE| is -0.0338 (t-stat=-1.48). The result implies that the salience effect is weaker in stocks with high investor attention.

[Table 7]

4.4 Retail Ownership and the Salience Effect

Having confirmed the existence of the salience effect in our data sample, we now investigate whether the ST value predictive power changes with retail ownership of ST stocks. This analysis is motivated by studies associating the impact of asset pricing anomalies stronger for stocks with high retail ownership (Han and Kumar, 2013; Lin and Liu, 2018). Following this mechanism, Bali et al. 2021 demonstrate that the lottery anomaly becomes more pronounced when retail investors own more lottery stocks. Retail ownership can hinder arbitrage by decreasing the availability of stocks in the short-selling market (Nagel et al., 2005). Since retail investors are assumed to be unsophisticated and tend to focus more on unusual salient features, we expect the salience effect to be more substantial for highly retail-owned stocks.

At the end of each month, all stocks are grouped into tercile portfolios according to their retail ownership and then sorted into decile portfolios based on ST value. Table 8 reports the FF5 alpha for the equal-weighted and value-weighted portfolios. The FF5 alpha spread between the high-ST and low-ST deciles within each RHLD portfolio is reported in the last row. The results show that for stocks in the high RHLD group, the monthly FF5 alpha spread in the EW portfolios is -1.06% per month with a t-statistics of -5.55, while for stocks in the low-RHLD group, the monthly FF5 alpha spread is -0.44% per month with a t-statistics of -2.89. Similarly, for the value-weighted portfolio, the FF5 alpha spread between high-ST and low-ST of the high RHLD group is -0.99% per month (t-stats=-4.95), whereas for the low RHLD group, the FF5 alpha spread between decile 10 and 1 is -0.36% per month (t-stats=-2.56). These results indicate that the salience effect is stronger and more dominant in stocks with high retail ownership but less robust in stocks with low retail ownership.

[Table 8]

To examine the impact of retail ownership on the salience effect while simultaneously controlling for other well-known predictors of future returns, we test the hypothesis by interacting ST value with retail holdings (RHLD) at the firm level using the Fama and Macbeth (1973) regressions. We conduct monthly cross-sectional regressions based on the following model specifications:

$$ExR_{i,t+1} = \lambda_{0,t} + \lambda_{1,t}\mathrm{ST}_{i,t} + \lambda_{2,t}(\mathrm{ST}_{i,t} \times \mathrm{RHLD}_{i,t}) + \lambda_{3,t}\mathrm{X}_{i,t} + \varepsilon_{i,t+1} \tag{8}$$

where $ExR_{i,t+1}$ is the excess return on stock *i* in month t+1, $\mathrm{ST}_{i,t}$ denotes proxy for salience theory value of stock i in month t, $\mathrm{RHLD}_{i,t}$ denotes proxy for retail ownership of stock i in month t and $\mathrm{X}_{i,t}$ is a vector of control variables.

Table 9 presents the results of the Fama-Macbeth regression, which includes the interaction terms between retail holdings and ST value. The interaction variables in specifications (1) and (2) are negative and statistically significant, indicating that high retail ownership strengthens the salience effect. Columns 1 and 2 show that the interacting ST value and retail investors, while including the control variables, generate an estimated coefficient of -0.0984 (t-stat=-7.57) and -0.0749 (t-stat=-4.35), respectively. Our regression results correspond with our portfolio results, indicating that the negative relation between salience and future returns is stronger among stocks with higher retail investors.

[Table 9]

Next, we partitioned our sample period into three groups based on tercile breakpoints of low, medium, and high retail investors. Then, we conduct monthly Fama-Macbeth regressions as in model 6. Table 10 reports the estimated coefficients of the Fama-Macbeth regressions of the monthly expected stock returns on ST values and other control variables under different retail holding levels. We find the results inconsistent with the bivariate portfolio sorts. The estimated coefficient of the ST value in the high retail ownership group is significant but smaller when compared to the low and medium RHLD groups. Column 3 shows that the estimated coefficient of high RHLD is -0.0645 with a t-statistic of -2.93, whereas the estimated coefficient for low RHLD is -0.0978 with a t-statistic of -3.90. These results demonstrate that the salience effect exists across the retail ownership groups. However, the salience effect is significantly strengthened among stocks with high retail ownership.

[Table 10]

4.5 Social Interaction and the Salience Effect

In this section, we examine the effect of social connectedness of the firm's headquarters locations on the salience effect. This is motivated by Bali et al. (2021) and Han, Hirshleifer, and Walden (2021) findings, which show that the intensity of social interactions increases retail investors' attraction to lottery stocks. Furthermore, Kuchler et al. (2022) document that social connectedness increases investors' awareness of less famous and small-size firms. The studies explain that retail investors tend to invest in stocks of firms whose headquarters are closer to them because their social connections make them more likely to know and have better information about these stocks. We, therefore, argue that the intensity of social interactions stimulates investors' awareness and attraction to ST stocks.

Table 11 reports the FF5 alphas for the EW and VW portfolios sorted by ST and each of the two social interaction proxies (SOCIAL). The difference in the returns between the high-ST and low-ST deciles within each social interaction-based group is reported in the last row of the table. Panel A shows that the salience effect returns are strong and statistically significant across the low, medium, and high SCIH groups. For the EW portfolios, the monthly FF5 alpha spread between decile 10 and decile 1 of the ST-sorted portfolios in the low, medium, and high SCIH are -0.76% per month (t-stats=-4.05), -0.83% per month (t-stats=-5.39) and -0.75% per month (t-stats=-4.34) respectively. The FF5 alpha spread between decile 10 and decile 1 of the ST-sorted VW portfolios in the low, medium, and high SCIH groups are -0.68% per month (t-stats=-3.59), -0.75% per month (t-stats=-4.60) and -0.70% per month (t-stats=-3.92) respectively. The results suggest that the predictive power of the ST value may not vary with the intensity of Facebook's social connectedness index but shows the crucial role social interaction plays in attracting retail investors and enhancing the salience effect.

Panel B reports the FF5 alphas for each EW and VW portfolio sorted by ST value and population density, a social interaction proxy. We find that the salience effect is amplified for stocks in more populated areas (high PD). For EW portfolios, the FF5 alpha spread between decile 10 and decile 1 of the ST-sorted portfolio is -0.89% per month (t-stats=-5.09) for stocks in the high PD group, and -0.79% per month (t-stats=-4.53) in the low PD group. In summary, our findings imply that intense social interaction influences investor attraction to ST stocks and enhances the salience effect.

[Table 11]

To examine the impact of social interaction on the salience effect while simultaneously controlling for other well-known predictors of future returns, we test the hypothesis by interacting with each social interaction proxy with ST at the firm level using the Fama and Macbeth (1973) regressions. We conduct monthly cross-sectional regressions based on the following model specifications:

$$ExR_{i,t+1} = \lambda_{0,t} + \lambda_{1,t}\mathrm{ST}_{i,t} + \lambda_{2,t}(\mathrm{ST}_{i,t} \times \mathrm{SOCIAL}_{i,t}) + \lambda_{3,t}\mathrm{X}_{i,t} + \varepsilon_{i,t+1} \qquad (9)$$

where $ExR_{i,t+1}$ is the excess return on stock i in month t+1, $\mathrm{ST}_{i,t}$ denotes proxy for salience theory value of stock i in month t, $\mathrm{SOCIAL}_{i,t}$ denotes proxy for social interaction to stock i in month t and $\mathrm{X}_{i,t}$ is a vector of control variables.

Table 12 presents the Fama-Macbeth regression results, including the interaction terms between each social interaction proxy and ST value. We find that the interaction variables in specifications (1) and (2) are negative and statistically significant, indicating that the intensity of social interaction strengthens the salience effect. Columns 1 and 2 show that including the interaction term between ST value and each of the social proxies (SCIH and PD) generates an estimated coefficient of -0.1006 (t-stat=-5.89) and -0.0752 (t-stat=-4.38), respectively. Table 11 also reports that the estimated coefficient of the interaction terms between SCIH and ST value is -0.0010 (t-stats=-1.96) and -0.0010 (t-stats=-1.91) for interaction between PD and ST value. Our regression result is consistent with the portfolio analysis results, indicating that social interaction enhances the salience effect.

[Table 12]

Next, we partitioned our sample period into three groups based on tercile low, medium, and high social interaction proxy breakpoints. Then, we conduct monthly Fama-Macbeth regressions as in model 6. Table 13 reports the estimated coefficients of the Fama-Macbeth regressions of the monthly expected stock returns on ST values and other control variables under different intensities of social interaction levels. Consistent with the portfolio analysis results, we find the estimated coefficients of ST values in the low, medium, and high SCIH-based groups are robust and significant regardless of the levels. Panel A shows an estimated coefficient of -0.795 (t-stats=-3.63), -0.0899 (t-stats=-4.20), and -0.0877 (t-stats=-3.57) in the low, medium, and high SCIH-based groups, respectively. The result suggests the supporting role of social interaction in enhancing the salience effect. Our regression analysis demonstrates that salience anomaly is strengthened with more intense social interactions.

[Table 13]

4.6 Robustness Test

Having established that investor attention, retail investors, and social interactions play an important role in the negative relationship between ST value and future stock returns, we conduct additional robustness tests to understand whether the results we documented in the previous sections corroborate with different periods of uncertainty (EPU) and ambiguity.

4.6.1 Economic Policy Uncertainty

Next, we examine whether the predictive power of salience theory value changes with different EPU periods. This study is motivated by existing literature that attributes the predictive power of asset pricing anomalies to economic and financial uncertainties (Baker et al., 2016). Building on the extant studies, Cakici and Zaremba (2022) argue that periods of high global uncertainty can intensify investors' concerns about salient downsides and disrupt arbitrage activities. Additionally, Pastor and Veronesi (2012) show that high EPU periods are frequently associated with significantly higher risk premia and higher stock return volatility. In this section, we run the Fama-Macbeth regressions over high and low EPU periods. We define high (low) EPU as periods when the economic policy uncertainty index in the previous month is above (below) the median value for the sample period spanning from January 1980 to December 2022. Table 14 Panel A shows that high EPU periods enhance the negative relation between ST value and future stock returns. In column 2, the average coefficient of ST value is larger and significantly negative (-0.1014 with a t-statistics of -3.95) for high EPU periods, and column 1 shows the average coefficient of ST value is -0.0503 (t-stats=-2.18) in the low EPU periods. This result indicates that the salience effect is stronger during periods of high EPU.

[Table 14]

4.6.2 Quality of Political Signal

Finally, we test the time-series effect of the quality of the political signal (QIN) on the salience effect. The theoretical model of Pastor and Veronesi (2012, 2017) argues that the impact of political shocks on stock prices and market volatility is higher when political signals are more precise and when there is greater policy uncertainty. This shows that investors are reluctant to update their beliefs and are hesitant to react in the financial markets when confronted with poor political signals (Bialkowski et al., 2022). In this section, we run the Fama-Macbeth regressions over different periods of high QIN and low QIN. We define high (low) QIN as periods when the value of Qindex is above (below) the median value for the sample period spanning from January 2000 to May 2020.

The higher the value of Qindex, the lower the quality of political signals. The results in Table 14 Panel B show that the salience effect is stronger in low Qindex periods. In column 1, the average coefficient of the ST value is larger and significantly negative (-0.0783 with a t-statistics of -2.25) for low QIN periods, and column 2 shows the average coefficient of ST is -0.0674 (t-stats=-1.86) in the high QIN periods. This result indicates that high-quality political signals weaken the negative relationship between salience and future stock returns.

5. CONCLUSION

In this study, we provide empirical analysis supporting evidence of a negative relationship between ST value and future stock returns in the cross-section of US stocks. This study also examines how investor attention, retail ownership, and social interactions contribute to the literature that explains the negative relationship between salience theory and future stock returns. Following Cosemans and Frehen (2021), we first re-examined the salience effect in the US stock market over a different sample period from January 1980 to December 2022. Our findings support the evidence of a robust and significant salience effect in the US stock market, even after controlling for well-known return predictors. Furthermore, we find that the salience effect is distinct from investor attention, which is stronger when investor attention is low. Our result further shows that the negative relation between salience and future stock returns is driven by high retail ownership, which is attributable to limited attention, the unsophisticated nature of retail investors, and their tendency to be more attracted to salient features of these stocks. As these retail investors tend to be influenced by social interactions, intense social interactions enhance the predictive power of salience in its negative relationship with future stock returns. Our results highlight the empirical evidence corroborating our hypothesis that investor attention, retail ownership, and social interactions play a significant role in investor attraction to ST stocks.

We conduct additional analysis to check whether the salience effect varies with uncertainty periods. Consistent with previous studies, we find that ST's predictive power on future stock returns is larger during periods of high economic policy uncertainty (EPU) and high-quality political signals.

References

Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. Journal of Financial Markets, 5(1), 31–56. https://doi.org/10.1016/S1386-4181(01)00024-6

Ang, A., Hodrick, R. J., Xing, Y., and Zhang, X. (2009). High idiosyncratic volatility and low returns: international and further U.S. evidence. Journal of Financial Economics, 91(1), 1–23. https://doi.org/10.1016/j.jfineco.2007.12.005

Bailey, M., Cao, R., Kuchler, T., Stroebel, J., Wong, A., 2018b. Social connectedness: measurement, determinants, and effects. J. Econ. Perspect. 32 (3), 259–280.

Bailey, M., Gupta, A., Hillenbrand, S., Kuchler, T., Richmond, R., Stroebel, J., 2021. International trade and social connectedness. J. Int. Econ. 129, 103418.

Bali, T. G., Cakici, N., and Whitelaw, R. (2011). Maxing out: stocks as lotteries and the cross-section of expected returns. Journal of Financial Economics, 99(2), 427–446. https://doi.org/10.1016/j.jfineco.2010.08.014

Bali, T., Hirshleifer, D., Peng, L., & Tang, Y. (2021). Attention, social interaction, and investor attraction to lottery stocks. National Bureau of Economic Research. https://doi.org/10.3386/w29543.

Baker, S. R., Bloom, N., and Davis, S. J. (2016). Measuring Economic Policy Uncertainty. The Quarterly Journal of Economics, 131(4), 1593–1636. https://doi.org/10.1093/qje/qjw024

Barber, B., and T. Odean. 2008. All that glitters: The effect of attention on the buying behavior of individual and institutional investors. Review of Financial Studies 21:785–818.

Barber, B., R. Lehavy, M. McNichols, and B. Trueman, (2001). "Can Investors Profit from the Prophets? Consensus Analyst Recommendations and Stock Returns," Journal of Finance 56,531-563.

Bialkowski, J., Dang, H.D., Wei, X., 2022. High policy uncertainty and low implied market volatility – an academic puzzle? Journal of Financial Economics, 143(3): 1185-1208.

Bordalo, P., Gennaioli, N., & Shleifer, A. (2012). Salience theory of choice under risk. Quarterly Journal of Economics, 127(3), 1243–1285. https://doi.org/10.1093/qje/qjs018. Oxford Academic.

Bordalo, P., Gennaioli, N., & Shleifer, A. (2013a). Salience and asset prices. American Economic Review, 103(3), 623–628. https://doi.org/10.1257/AER.103.3.623.

Bordalo, P., Gennaioli, N., & Shleifer, A. (2013b). Salience and consumer choice. Journal of Political Economy, 121(5), 803–843. https://doi.org/10.1086/673885.

Bordalo, P., Gennaioli, N., & Shleifer, A. (2015). Salience theory of judicial decisions. The Journal of Legal Studies, 44(S1), S7–S33. https://doi.org/10.1086/676007. University of Chicago Press.

Brandt, M.W., Brav, A., Graham, J., and Kumar, A. (2010). The idiosyncratic volatility puzzle: time trend or speculative episodes? Review of Financial Studies, 23(2), 863–899. https://doi.org/10.1093/rfs/hhp087

Brown, J., Ivković, Z., Smith, P., and S. Weisbenner (2008). 'Neighbors Matter: Causal Community Effects and Stock Market Participation.' Journal of Finance. 63, 1509-31.

Carhart, M., (1997). On persistence in mutual fund performance, Journal of Finance 52, 57–82.

Cai, C. X., & Zhao, R. (2022). Salience theory and cryptocurrency returns. SSRN Electronic Journal. https://doi.org/10.2139/SSRN.3983602.

Cakici, N., & Zaremba, A. (2021). Salience theory and the cross-section of stock returns: International and further evidence. Journal of Financial Economics. https://doi.org/10.1016/J.JFINECO.2021.10.010. North-Holland.

Chetty, R., Looney, A., Kroft, K., (2009). Salience and taxation: theory and evidence. Am. Econ. Rev. 99, 1145–1177.

Cohen, L., and A. Frazzini. 2008. Economic links and predictable returns. Journal of Finance 63:1977–2011.

Cosemans, M., & Frehen, R. (2021). Salience theory and stock prices: Empirical evidence. Journal of Financial Economics, 140(2), 460–483. https://doi.org/10.1016/j. jfineco.2020.12.012. Elsevier B.V.

Duggan, M., N. B. Ellison, C. Lampe, A. Lenhart, and M. Madden. (2015). Demographics of key social networking platforms. Pew Research Center.

Fama, E. F., and French, K. R. (1992). The cross-section of expected stock returns. Journal of Finance, 47(2), 427–465. https://doi.org/10.1111/j.1540-6261.1992.tb04398.x

Fama, E. F., and French, K. R. (1993). Common risk factors in the returns of stocks and bonds. Journal of Financial Economics, 33(1), 3–56. https://doi.org/10.1016/0304-405X(93)90023-5

Fama, E. F., and MacBeth. J.D. (1973). Risk, Return, and Equilibrium: Empirical Tests. The Journal of Political Economy, 81(3), 607-636. https://doi.org/10.1017/CBO9781107415324.004.

Fama, E.F., French, K.R., (2015). A five-factor asset pricing model. Journal of Financial Economics, 116, 1–22.

Gilbert, T., S. Kogan, L. A. Lochstoer, and A. Ozyildirim. 2012. Investor inattention and the market impact of summary statistics. Management Science 58:336–50.

Han, B., & Kumar, A. (2013). Speculative retail trading and asset prices. Journal of Financial and Quantitative Analysis, 48(2), 377-404.

Hirshleifer, D., S. Lim, and S. H. Teoh. 2009. Driven to distraction: Extraneous events and underreaction to earnings news. Journal of Finance 64:2289–325.

Hirshleifer, D. 2020. Presidential address: Social transmission bias in economics and finance. Journal of Finance 75:1779–831.

Hong, H., Kubik, J. D., and J. C. (2004). Stein 'Social Interaction and Stock-Market Participation.' Journal of Finance. 59, 137-63.

Hong, H., J. Kubik, and J. Stein. 2008. The only game in town: Stock-price consequences of local bias. Journal of Financial Economics 90:20–37.

Hou, K., Xue, C., and Zhang, L. (2015). Digesting anomalies: an investment approach. *Review of Financial Studies*, 28(3), 650–705. https://doi.org/10.1093/rfs/hhu068

Nguyen, H. T., & Pham, M. H. (2021). Does investor attention matter for market anomalies?. *Journal of Behavioral and Experimental Finance*, 29, 100451.

Hur, J., Singh, V. (2022). The role of investor attention in idiosyncratic volatility puzzle and new results. Rev Quant Finan Acc 58, 409–434. https://doi.org/10.1007/s11156-021-00999-w.

Kaniel, R., and R. Parham. (2017). WSJ category kings — The impact of media attention on consumer and mutual fund investment decisions. *Journal of Financial Economics* 123:337–56.

Kuchler, T., Li, Y., Peng, L., Stroebel, J., & Zhou, D. (2022). Social proximity to capital: Implications for investors and firms. *The Review of Financial Studies*, 35(6), 2743-2789.

Lehmann, B. N. (1990). Fads, Martingales, and Market Efficiency. *The Quarterly Journal of Economics*, 105(1), 1-28. https://doi.org/10.2307/2937816

Lin, T. C., & Liu, X. (2018). Skewness, individual investor preference, and the cross-section of stock returns. *Review of Finance*, *22*(5), 1841-1876.

Lin, T. C., & Zhang, Y. (2022). Salience Theory and Corporate Bond Pricing. *Available at SSRN* 4228611.

Liu, C., Sun, P., & Zhu, D. (2023). Lottery preference, short-sale constraint, and the salience effect: Evidence from China. *Economic Modelling*, 125, 106341.

Jegadeesh, N., and Titman, S. (1993). Returns to buying winners and selling losers: implications for stock market efficiency. *Journal of Finance*, 48(1), 65–91. https://doi.org/10.1111/j.1540-6261.1993.tb04702.x.

Nagel, S., (2005). Short sales, institutional investors, and the cross-section of stock returns, *Journal of Financial Economics* 78, 277–309.

Newey, W.K., and West, K.D., (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance

matrix. *Econometrica*, 55(3), 703–708. https://doi.org/10.2307/1913610

Pastor, L and P Veronesi (2012). "Uncertainty about government policy and stock prices," *Journal of Finance* 67: 1219-1264.

Pastor, L., & Veronesi, P. (2017). Explaining the puzzle of high policy uncertainty and low market volatility. *Vox Column*, *25*.

Peng, L., & Xiong, W. (2006). Investor attention, overconfidence and category learning. *Journal of Financial Economics*, *80*(3), 563-602. https://doi.org/10.1016/j.jfineco.2005.05.003.

Rehbein, O., & Rother, S. (2020). The role of social networks in bank lending (No. 033). ECONtribute Discussion So, R. H., & Zhang, X. (2024). Salience Theory and Equity Option Returns. *Available at SSRN 4707064*. http://dx.doi.org/10.2139/ssrn.4707064.

Table 1. Descriptive Statistics

This table reports the descriptive statistical summary in Panel A and Pearson's pairwise correlation coefficients of the main variables used in this study in Panel B. This includes the salience theory value (ST), the current stock return (RET), the investor attention proxies- the absolute abnormal monthly return (ABNRET), and the abnormal monthly trading volume (ABNVOL). The retail holding is the percentage of shares held by retail investors (RHLD). The social interaction proxies are the Facebook Social Connectedness Index (SCIH) and Population Density (PD). The control variables include the market beta (BETA), log of market capitalization (SIZE), book-to-market (BETA), momentum (MOM), short-term reversal (REV), maximum daily return (MAX), idiosyncratic volatility (IVOL), illiquidity (ILLIQ), log of stock price (PRICE) and asset growth (AG). All variables are winsorized at the 1st and 99th percentiles. The sample period is from January 1980 to December 2022.

Panel A: Summary statistics

	N	Mean	SD	Skewness	Min	Median	Max
RET	927401	0.0149	0.1257	1.4216	-0.8750	0.0089	5.7694
ST	927401	0.0045	0.0227	1.3658	-0.2465	0.0030	1.1518
CVRG	927401	3.8302	3.9193	2.1621	1.0000	2.0000	46.0000
SUE	927401	0.9985	1.2615	3.1917	0.0082	0.5997	8.4853
RHLD	927401	48.1889	27.5204	0.0645	0.0003	47.5088	99.0349
SCIH	927401	2.1863	0.6775	0.6776	1.0639	2.1189	6.2455

PD	927401	4.8442	13.6564	4.2910	0.0228	1.4624	71.6998
BETA	927401	1.0993	0.6977	0.9449	-14.3628	1.0227	9.0351
SIZE	927401	6.3378	1.8617	0.4123	1.0275	6.1459	11.0055
BM	927401	0.4988	0.4280	1.8829	0.0169	0.4119	3.2138
MOM	927401	0.1940	0.5071	1.8488	-0.8086	0.1107	2.5480
REV	927401	0.0174	0.1220	0.6519	-0.3750	0.0102	0.5347
MAX	927401	0.0559	0.0437	2.8782	0.0055	0.0438	0.4000
IVOL	927401	0.0196	0.0132	3.4902	0.0054	0.0164	0.9130
ILLIQ	927401	0.0214	0.0836	21.4953	0.0069	0.0023	4.8875
PRICE	927401	3.0964	0.7827	0.3423	1.6448	3.0773	5.2914
AG	927401	0.0091	0.0487	5.6376	-0.0534	0.0023	0.3590

Panel B: Pearson's pairwise correlation matrix

Variables	ST	CVRG	SUE	RHLD	SCIH	PD	BETA	SIZE	BM	MOM	REV	MAX	IVOL	ILLIQ	ROE	AG
ST	1.000															
CVRG	-0.032***	1.000														
SUE	-0.005***	0.003***	1.000													
RHLD	0.065***	-0.311***	-0.010***	1.000												
SCIH	-0.029***	-0.044***	-0.007***	0.088***	1.000											
PD	0.000	0.049***	-0.001	-0.032***	-0.250***	1.000										
BETA	0.061***	0.110***	0.004***	-0.163***	-0.159***	0.022***	1.000									
SIZE	-0.051***	0.521***	0.003***	-0.595***	-0.032***	0.099***	0.045***	1.000								
BM	0.024***	-0.188***	-0.013***	0.278***	0.095***	-0.002**	-0.100***	-0.369***	1.000							
MOM	0.001	-0.053***	-0.020***	0.033***	-0.028***	-0.008***	0.067***	0.026***	-0.054***	1.000						
REV	-0.012***	-0.023***	-0.018***	0.029***	-0.010***	-0.002**	0.023***	0.002*	0.044***	0.265***	1.000					
MAX	0.587***	-0.079***	0.043***	0.098***	-0.076***	-0.022***	0.198***	-0.202***	-0.012***	0.028***	-0.034***	1.000				
IVOL	0.289***	-0.121***	0.053***	0.193***	-0.079***	-0.037***	0.187***	-0.335***	0.005***	0.056***	-0.010***	0.821***	1.000			
ILLIQ	0.048***	-0.216***	-0.003**	0.293***	0.019***	-0.012***	-0.079***	-0.342***	0.213***	0.064***	0.047***	0.104***	0.161***	1.000		
PRICE	-0.024***	0.310***	0.003***	-0.415***	0.033***	0.058***	-0.113***	0.708***	-0.269***	0.139***	0.048***	-0.247***	-0.369***	-0.233***	1.000	
AG	0.007***	0.015***	0.036***	0.006***	-0.011***	-0.003***	0.016***	0.001	-0.031***	0.045***	0.011***	0.009***	0.013***	-0.007***	0.020***	1.000

Panel C: Spearman's rank correlation coefficients

Variables	STV	CVRG	SUE	RHLD	SCIH	PD	BETA	SIZE	BM	MOM	REV	MAX	IVOL	ILLIQ	PRICE	AG
ST	1.000															
CVRG	-0.021***	1.000														
SUE	-0.005***	-0.002*	1.000													
RHLD	0.054***	-0.319***	-0.018***	1.000												
SCIH	-0.027***	-0.042***	-0.002	0.077***	1.000											
PD	0.002**	0.060***	-0.007	-0.131***	-0.513***	1.000										
BETA	0.059***	0.1263***	0.003***	-0.181***	-0.161***	0.076***	1.000									
SIZE	-0.047***	0.533***	0.014***	-0.630***	-0.029***	0.126***	0.068***	1.000								
BM	0.014***	-0.204***	-0.024***	0.324***	0.107***	-0.111***	-0.135***	-0.405***	1.000							
MOM	-0.026***	-0.034***	-0.017***	0.008***	-0.004***	0.003***	-0.023***	0.079***	-0.057***	1.000						
REV	-0.025***	-0.008***	-0.013***	0.009***	-0.002*	0.002	0.002	0.028***	0.027***	0.257***	1.000					
MAX	0.475***	-0.085***	0.037***	0.108***	-0.086***	-0.005***	0.244***	-0.257***	-0.035***	-0.091***	-0.071***	1.000				
IVOL	0.191***	-0.135***	0.039***	0.222***	-0.084***	-0.024***	0.218***	-0.412***	-0.003***	-0.082***	-0.054***	0.825***	1.000			
ILLIQ	0.074***	-0.520***	-0.012***	0.699***	0.057***	-0.128***	-0.119***	-0.937***	0.424***	0.026***	0.023***	0.233***	0.376***	1.000		
PRICE	-0.023***	0.327***	0.018***	-0.410***	0.042***	0.056***	-0.103***	0.706***	-0.267***	0.225***	0.079***	-0.327***	-0.459***	-0.627***	1.000	
AG	-0.004	0.017***	0.019***	0.005***	0.003***	-0.008***	-0.012***	0.015***	-0.002**	0.037***	0.012***	-0.020***	-0.026***	-0.009***	0.043***	1.000

Table 2. Characteristics of ST-sorted portfolios.

This table reports the characteristics of portfolios formed based on the salience theory value (ST). At the end of each month, stocks are sorted into decile portfolios based on their ST value, and then we calculate the equal-weighted average of the firm's characteristics. The various characteristics variables include the investor attention proxies-analyst coverage (CVRG)and the absolute value of the standardized quarterly unexpected earnings (|SUE|); the the percentage of shares held by retail investors (RHLD), the social interaction proxies- the Facebook Social Connectedness Index (SCIH) and Population Density (PD); the market beta (BETA), log of market capitalization (SIZE), book-to-market (BETA), momentum (MOM), short-term reversal (REV), maximum daily return (MAX), idiosyncratic volatility (IVOL), illiquidity (ILLIQ), log of stock price (PRICE) and asset growth (AG). The sample period is from January 1980 to December 2022.

Decile	CVRG	SUE	RHLD	SCIH	PD	BETA	SIZE	BM	MOM	REV	MAX	IVOL	ILLIQ	PRICE	AG
Low ST	0.912	1.100	0.500	2.131	4.443	1.284	5.817	0.489	0.231	0.024	0.050	0.027	0.028	2.803	1.003
	(104.15)	(78.00)	(66.24)	(668.09)	(75.66)	(167.09)	(150.11)	(68.78)	(18.27)	(8.45)	(71.94)	(99.89)	(28.76)	(246.44)	(10.94)
2	0.959	0.999	0.492	2.194	4.887	1.108	6.222	0.521	0.181	0.020	0.040	0.017	0.022	3.049	0.892
	(108.33)	(71.12)	(68.86)	(864.46)	(88.85)	(166.99)	(163.06)	(71.19)	(18.90)	(8.97)	(67.62)	(92.59)	(30.04)	(259.76)	(10.35)
3	0.998	0.963	0.492	2.218	5.103	1.022	6.426	0.532	0.168	0.018	0.037	0.015	0.019	3.173	0.881
	(110.83)	(72.79)	(71.81)	(864.79)	(88.24)	(154.79)	(178.53)	(72.81)	(19.51)	(8.94)	(68.71)	(92.91)	(31.30)	(294.99)	(10.34)
4	1.003	0.954	0.496	2.231	5.168	0.979	6.504	0.539	0.167	0.018	0.036	0.013	0.018	3.229	0.845
	(113.80)	(73.52)	(73.27)	(918.75)	(95.49)	(147.54)	(178.15)	(75.47)	(20.27)	(9.68)	(68.53)	(91.14)	(31.27)	(310.52)	(10.27)
5	1.008	0.960	0.496	2.231	5.229	0.977	6.535	0.536	0.167	0.017	0.037	0.013	0.018	3.246	0.840
	(112.48)	(72.07)	(73.10)	(910.52)	(88.83)	(147.32)	(179.78)	(73.81)	(20.35)	(9.09)	(68.45)	(84.40)	(30.12)	(308.01)	(10.08)
6	1.011	0.957	0.490	2.224	5.248	1.006	6.521	0.532	0.165	0.016	0.042	0.014	0.018	3.235	0.864
	(120.40)	(74.19)	(72.28)	(911.18)	(87.10)	(155.90)	(177.84)	(74.44)	(19.54)	(8.24)	(69.45)	(81.68)	(29.30)	(311.22)	(9.94)
7	1.000	0.964	0.485	2.205	5.235	1.052	6.463	0.526	0.168	0.015	0.049	0.016	0.019	3.204	0.916
	(118.90)	(71.12)	(71.05)	(923.27)	(86.34)	(164.79)	(176.80)	(72.29)	(18.70)	(7.13)	(71.14)	(78.81)	(30.04)	(293.75)	(10.63)
8	0.969	0.988	0.488	2.181	5.153	1.125	6.328	0.522	0.174	0.013	0.058	0.018	0.021	3.133	0.918
	(121.95)	(73.88)	(69.45)	(888.35)	(81.53)	(182.93)	(172.08)	(72.87)	(18.06)	(5.96)	(73.95)	(79.00)	(29.62)	(278.64)	(10.46)
9	0.902	0.988	0.500	2.148	4.901	1.224	6.084	0.519	0.187	0.012	0.074	0.022	0.026	3.015	0.952
	(124.58)	(77.95)	(67.79)	(768.81)	(76.44)	(198.51)	(161.30)	(70.76)	(16.91)	(4.70)	(77.20)	(82.20)	(28.19)	(273.02)	(10.70)
High ST	0.784	1.040	0.542	2.087	4.606	1.378	5.678	0.519	0.215	0.011	0.127	0.034	0.039	2.816	0.967
	(104.04)	(79.51)	(69.96)	(594.94)	(75.40)	(171.33)	(149.06)	(69.22)	(14.99)	(3.49)	(95.46)	(95.97)	(27.40)	(284.95)	(10.64)
High-Low	-0.128	-0.0600	0.0413	-0.0436	0.163	0.0941	-0.139	0.0303	-0.0158	-0.012	0.076	0.007	0.011	0.013	-0.036
	(-15.51)	(-7.65)	(22.25)	(-9.15)	(2.23)	(7.49)	(-9.17)	(7.57)	(-2.38)	(-8.71)	(87.38)	(31.99)	(13.23)	(1.92)	(-1.26)

Table 3: Returns on ST-Sorted Portfolios

This table reports raw excess returns and alphas for decile portfolios formed on the salience theory variable ST. At the end of each month, stocks are sorted into decile portfolios based on their ST value. Portfolio 1 (10) contains the stocks with the lowest (highest) ST value. Portfolios are rebalanced at the end of the following month, and their realized return is recorded. For each decile portfolio, we report the equal-weighted (EW) and value-weighted (VW) average monthly excess return, Fama-French three-factor, Cahart four-factor, FF 5-factor, and five-factor alpha obtained from the FF-Cahart model augmented with the PS liquidity factor. The last row reports differences in monthly returns and alphas between quintile 5 (high ST) and quintile 1 (low ST). Corresponding t-statistics in parentheses are based on Newey and West (1987) standard errors with 6 lags. The sample period is January 1980 to December 2022.

EW Portfolios							VW Portfolios					
Decile	Ret-Rf	α3	α4	α5	α5_PS	α7	Ret-Rf	α3	α4	α5	α5_PS	α7
Low ST	0.0110	0.0107	0.0113	0.0123	0.0115	0.0129	0.0109	0.0104	0.0109	0.0119	0.0111	0.0125
	(4.23)	(4.15)	(4.17)	(4.50)	(4.07)	(4.34)	(4.05)	(3.96)	(4.00)	(4.33)	(3.89)	(4.17)
2	0.0120	0.0111	0.0115	0.0119	0.0116	0.0124	0.0112	0.0107	0.0112	0.0116	0.0113	0.0121
	(4.96)	(4.85)	(4.95)	(4.79)	(4.79)	(4.69)	(4.88)	(4.74)	(4.85)	(4.74)	(4.70)	(4.64)
3	0.0109	0.0102	0.0107	0.0110	0.0108	0.0116	0.0106	0.0100	0.0104	0.0108	0.0106	0.0113
	(4.89)	(4.65)	(4.79)	(4.65)	(4.69)	(4.66)	(4.90)	(4.63)	(4.74)	(4.63)	(4.62)	(4.59)
4	0.0099	0.0092	0.0098	0.0097	0.0100	0.0104	0.0098	0.0091	0.0097	0.0097	0.0099	0.0103
	(4.81)	(4.59)	(4.85)	(4.48)	(4.73)	(4.57)	(4.84)	(4.58)	(4.82)	(4.50)	(4.70)	(4.57)
5	0.0097	0.0090	0.0096	0.0094	0.0097	0.0100	0.0094	0.0089	0.0094	0.0093	0.0096	0.0099
	(4.54)	(4.33)	(4.51)	(4.23)	(4.41)	(4.27)	(4.58)	(4.35)	(4.51)	(4.26)	(4.42)	(4.30)
6	0.0087	0.0081	0.0087	0.0087	0.0088	0.0094	0.0085	0.0080	0.0086	0.0086	0.0087	0.0092
	(4.10)	(3.92)	(4.13)	(3.97)	(4.04)	(4.04)	(4.09)	(3.90)	(4.10)	(3.98)	(4.00)	(4.01)
7	0.0084	0.0077	0.0083	0.0084	0.0084	0.0089	0.0082	0.0076	0.0082	0.0082	0.0083	0.0088
	(3.76)	(3.51)	(3.70)	(3.58)	(3.59)	(3.57)	(3.74)	(3.49)	(3.67)	(3.55)	(3.54)	(3.52)
8	0.0083	0.0075	0.0081	0.0080	0.0082	0.0086	0.0082	0.0076	0.0082	0.0080	0.0083	0.0086
	(3.54)	(3.30)	(3.46)	(3.35)	(3.34)	(3.31)	(3.57)	(3.33)	(3.47)	(3.36)	(3.35)	(3.30)
9	0.0063	0.0056	0.0062	0.0064	0.0063	0.0069	0.0064	0.0059	0.0064	0.0067	0.0065	0.0072
	(2.43)	(2.26)	(2.34)	(2.40)	(2.30)	(2.40)	(2.49)	(2.32)	(2.40)	(2.49)	(2.35)	(2.45)
High ST	0.0043	0.0035	0.0039	0.0045	0.0041	0.0050	0.0046	0.0039	0.0043	0.0049	0.0045	0.0054
	(1.47)	(1.24)	(1.29)	(1.49)	(1.32)	(1.53)	(1.55)	(1.33)	(1.38)	(1.60)	(1.41)	(1.63)
High-Low	-0.0070	-0.0072	-0.0074	-0.0078	-0.0074	-0.0079	-0.0063	-0.0065	-0.0066	-0.0070	-0.0066	-0.0071
t-stat	(-5.20)	(-5.01)	(-4.96)	(-5.22)	(-4.96)	(-5.26)	(-4.51)	(-4.34)	(-4.26)	(-4.52)	(-4.26)	(-4.52)

Table 4. Fama-Macbeth regression results of ST and stock returns

This table presents the estimated coefficients from the Fama-MacBeth cross-sectional regressions where we run the excess stock returns in month $_{t+1}$ on the ST value and a set of control variables. The control variables are the market beta (BETA), log of market capitalization (SIZE), book-to-market (BETA), momentum (MOM), short-term reversal (REV), maximum daily return (MAX), idiosyncratic volatility (IVOL), illiquidity (ILLIQ), log of stock price (PRICE) and asset growth (AG). Newey-West adjusted t-statistics are reported in parentheses. The sample period is from January 1980 to December 2022.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
ST	-9.0693***	-9.5260***	-9.4270***	-9.5540***	-9.0162***	-9.1379***	-4.1184**	-7.4871***	-9.3254***	-9.4342***	-9.0757***	-7.6533***
	(-6.31)	(-7.00)	(-6.42)	(-6.75)	(-6.66)	(-6.45)	(-1.98)	(-5.30)	(-6.46)	(-6.56)	(-6.32)	(-4.42)
BETA		0.0389										0.0971
		(0.27)										(0.85)
SIZE			-0.0420									-0.0187
			(-1.42)									(-0.68)
BM				0.2699**								0.1903**
				(2.25)								(2.08)
MOM					0.4812***							0.6941***
					(2.97)							(5.46)
REV						0.4018						-0.4957*
						(0.97)						(-1.82)
MAX							-4.9158***					0.0147
							(-2.82)					(0.01)
IVOL								-15.0319***				-22.0988***
								(-3.07)				(-5.48)
ILLIQ									0.1926			0.2713
									(0.25)			(0.27)
PRICE										-0.0779		-0.2068***
										(-0.95)		(-3.13)
AG											1.3695**	1.6963***
											(2.27)	(2.98)
cons	0.9342***	0.8922***	1.1924***	0.7477***	0.7806***	0.8641***	1.1544***	1.2001***	0.9099***	1.1668***	0.9371***	1.6396***
	(3.93)	(5.44)	(3.41)	(2.91)	(3.39)	(3.72)	(5.91)	(6.11)	(3.80)	(2.71)	(3.96)	(4.86)
Obs	927,401	927,401	927,401	927,401	927,401	927,401	927,401	927,401	927,401	927,401	927,401	927,401
R^2	0.004	0.029	0.013	0.012	0.019	0.012	0.016	0.016	0.008	0.015	0.006	0.068

Table 5: Bivariate portfolios of stocks sorted by Investor attention and ST

At the end of each month, stocks are grouped into three portfolios based on attention proxies, and then, within each portfolio, stocks are further sorted into decile portfolios based on their ST values. The three attention-based groups intersect with the decile ST-based groups to generate 30 equal-weighted (EW) and value-weighted (VW) portfolios. The portfolios are rebalanced at the end of the following month. We report the equal and value-weighted (VW) FF5 alphas for each ST-sorted decile portfolio. The last columns show the differences between decile 10 (high ST) and decile 1 (low ST) within each attention-based group. The attention proxies are the analyst coverage (CVRG) in Panel A and the absolute value of the standardized quarterly unexpected earnings (|SUE|) in Panel B. The Newey-West (1987) t-statistics are given in parentheses. The sample period is January 1980 to December 2022.

Panel A. Double-sorted on CVRG (Analyst Coverage) and ST

	Equal weighted portfolios				Value weighted portfolios			
ST	Low	Medium	High	AVG	Low	Medium	High	AVG
Low ST	1.335***	1.137***	1.055***	1.176***	1.299***	1.111***	1.024***	1.145***
	(5.12)	(3.89)	(3.63)	(3.89)	(4.90)	(3.80)	(3.56)	(3.76)
2	1.245***	1.299***	1.191***	1.245***	1.228***	1.289***	1.169***	1.227***
	(5.07)	(4.77)	(4.58)	(5.10)	(4.99)	(4.81)	(4.56)	(5.01)
3	1.044***	1.156***	1.051***	1.084***	1.039***	1.147***	1.028***	1.071***
	(4.46)	(4.66)	(4.25)	(4.95)	(4.46)	(4.71)	(4.26)	(4.93)
4	0.967***	1.017***	1.043***	1.009***	0.959***	1.018***	1.034***	1.004***
	(4.55)	(4.30)	(4.39)	(5.08)	(4.51)	(4.37)	(4.44)	(5.09)
5	0.946***	0.908***	0.916***	0.923***	0.931***	0.903***	0.906***	0.913***
	(4.45)	(3.73)	(3.92)	(4.66)	(4.40)	(3.81)	(3.95)	(4.66)
6	0.838***	0.881***	0.910***	0.876***	0.834***	0.850***	0.888***	0.857***
	(3.68)	(3.71)	(3.76)	(4.29)	(3.65)	(3.64)	(3.77)	(4.24)
7	0.916***	0.759**	0.899***	0.858***	0.889***	0.727**	0.886***	0.834**
	(3.79)	(3.18)	(3.72)	(4.06)	(3.68)	(3.08)	(3.76)	(3.97)
8	0.631*	0.793**	0.855***	0.759**	0.609*	0.810***	0.847***	0.755**
	(2.55)	(3.26)	(3.52)	(3.47)	(2.45)	(3.39)	(3.52)	(3.46)
9	0.551*	0.585*	0.837**	0.658*	0.555*	0.608*	0.832**	0.665*
	(1.99)	(2.12)	(3.00)	(2.61)	(1.98)	(2.22)	(3.02)	(2.61)
High ST	0.324	0.319	0.809*	0.484	0.362	0.373	0.803*	0.513
	(1.08)	(1.02)	(2.54)	(1.58)	(1.17)	(1.19)	(2.54)	(1.64)
High-Low	-1.011***	-0.818***	-0.245	-0.692***	-0.937***	-0.738***	-0.222	-0.632***
	(-6.26)	(-5.18)	(-1.30)	(-5.28)	(-5.71)	(-4.57)	(-1.16)	(-4.71)

Table 5 (continued)

Panel B. Double-sorted on SUE (Standardized unexpected earnings) and ST

	EW portfolios				VW portfolios			
ST	Low	Medium	High	AVG	Low	Medium	High	AVG
Low ST	1.491***	1.336***	0.899**	1.242***	1.384***	1.310***	0.918**	1.203***
	(5.33)	(4.73)	(3.28)	(4.10)	(4.90)	(4.66)	(3.29)	(3.90)
2	1.323***	1.158***	1.038***	1.173***	1.293***	1.127***	1.036***	1.152***
	(5.41)	(4.51)	(3.87)	(4.88)	(5.33)	(4.41)	(3.90)	(4.72)
3	1.204***	1.119***	0.972***	1.098***	1.182***	1.091***	0.976***	1.083***
	(5.23)	(4.73)	(3.86)	(5.09)	(5.25)	(4.66)	(3.94)	(5.00)
4	1.016***	0.983***	0.908***	0.969***	0.997***	0.960***	0.918***	0.958***
	(4.51)	(4.51)	(3.92)	(4.96)	(4.46)	(4.43)	(4.01)	(4.85)
5	1.003***	1.031***	0.763**	0.932***	0.959***	1.018***	0.783**	0.919***
	(4.60)	(4.62)	(3.17)	(4.74)	(4.48)	(4.67)	(3.27)	(4.68)
6	0.961***	0.903***	0.836***	0.900***	0.940***	0.898***	0.834***	0.890***
	(4.42)	(3.96)	(3.57)	(4.46)	(4.39)	(3.99)	(3.59)	(4.38)
7	0.842***	0.850***	0.791**	0.827***	0.817***	0.810***	0.815***	0.814***
	(3.52)	(3.70)	(3.26)	(3.95)	(3.47)	(3.57)	(3.43)	(3.86)
8	0.877***	0.758**	0.717**	0.784**	0.863***	0.761**	0.738**	0.787**
	(3.66)	(3.02)	(2.91)	(3.62)	(3.60)	(3.07)	(3.03)	(3.59)
9	0.625*	0.785**	0.554	0.655*	0.648*	0.786**	0.595*	0.676*
	(2.29)	(3.03)	(1.90)	(2.60)	(2.38)	(3.02)	(2.03)	(2.62)
High ST	0.596	0.351	0.401	0.449	0.625*	0.389	0.446	0.487
	(1.93)	(1.17)	(1.27)	(1.52)	(2.00)	(1.27)	(1.40)	(1.59)
High-Low	-0.896***	-0.985***	-0.498**	-0.793***	-0.759***	-0.921***	-0.471*	-0.716***
	(-5.52)	(-6.51)	(-2.68)	(-5.80)	(-4.61)	(-5.78)	(-2.48)	(-5.02)

Table 6: Fama-MacBeth regressions: Salience and Investor attention

This table reports the results of a Fama-MacBeth analysis of the impact of investor attention on the relation between a stock's salience theory value and future return. Monthly cross-sectional regressions are run of excess stock returns in month t + 1 on a firm's ST value and interaction terms between ST and attention proxies (ATTN) constructed at the end of the previous month t. The investor attention proxies (ATTN) are analyst coverage (CVRG) and the absolute value of the standardized quarterly unexpected earnings (|SUE|). The Newey-West (1987) t-statistics are given in parentheses. The sample period is January 1980 to December 2022.

	CVRG	SUE
Variables	(1)	(2)
ST	-0.0883***	-0.1021***
	(-5.05)	(-5.64)
ST × CVRG	0.0188**	
	(2.02)	
ST × SUE		0.0263***
		(2.98)
ATTN	0.0008**	-0.0013***
	(2.53)	(-7.50)
RHLD	-0.0028	-0.0036
	(-1.81)	(-2.24)
BETA	0.0007	0.0008
	(0.65)	(0.75)
SIZE	-0.0008**	-0.0003
	(-2.56)	(-1.22)
BM	0.0019**	0.0019**
	(2.09)	(2.09)
MOM	0.0073***	0.0069***
	(5.73)	(5.44)
ILLIQ	0.0073	0.0076
	(0.79)	(0.82)
MAX	-0.0016	0.0014
	(-0.00)	(0.10)
IVOL	-0.2213***	-0.2107***
	(-5.45)	(-5.21)
REV	-0.0052*	-0.0055**
	(-1.93)	(-2.03)
PRICE	-0.0021***	-0.0022***
	(-3.07)	(-3.22)
AG	0.0163***	0.0171***
	(2.90)	(3.07)
Cons	0.0206***	0.0211***
	(4.68)	(4.77)
Obs	927,401	927,401
Adj R^2	0.074	0.073

Table 7. Fama-MacBeth Regressions: ST Effect in Different Levels of Attention.

This table reports the estimated coefficients of the Fama-Macbeth regressions of the monthly expected stock returns on ST values and other control variables under different attention levels. We partition the sample periods into three groups based on the attention proxies. The high attention (low attention) is those in which the investor attention is above (below) the tercile breakpoint for the sample period. This table reports the ST effect on different attention levels. The attention proxies are the analyst coverage (CVRG)and the absolute value of the standardized quarterly unexpected earnings (|SUE|). The Newey-West (1987) t-statistics are given in parentheses. The sample period is January 1980 to December 2022.

	Low CVRG	Med CVRG	High CVRG	Chow Test	Low SUE	Med SUE	High SUE	Chow Test
Variables	(1)	(2)	(3)		(1)	(2)	(3)	
ST	-0.0773***	-0.0965***	-0.0483*	F-stat=25.53	-0.0873***	-0.1236***	-0.0338	F-stat=19.42
	(-3.88)	(-4.28)	(-1.78)	P value= 0.0000	(-3.93)	(-5.47)	(-1.48)	P value= 0.0000
RHLD	-0.0032*	-0.0024	-0.0037*		-0.0027	-0.0018	-0.0063***	
	(-1.71)	(-1.36)	(-1.77)		(-1.44)	(-0.97)	(-3.29)	
BETA	0.0015	0.0002	-0.0001		0.0015	0.0007	0.0002	
	(1.45)	(0.17)	(-0.10)		(1.33)	(0.56)	(0.16)	
SIZE	-0.0010**	-0.0002	-0.0005		-0.0006*	-0.0005*	0.0001	
	(-2.57)	(-0.55)	(-1.47)		(-1.79)	(-1.69)	(0.19)	
BM	0.0027***	0.0010	-0.0003		0.0011	0.0008	0.0036***	
	(3.19)	(0.85)	(-0.20)		(1.13)	(0.82)	(3.20)	
MOM	0.0081***	0.0064***	0.0068***		0.0048***	0.0045***	0.0104***	
	(6.43)	(3.99)	(4.31)		(3.21)	(3.27)	(7.06)	
ILLIQ	0.0049	0.0246	-0.3087**		0.0033	0.0069	0.0333**	
	(0.57)	(0.66)	(-2.05)		(0.23)	(0.38)	(2.36)	
MAX	-0.0051	0.0013	0.0154		-0.0288	0.0184	0.0040	
	(-0.29)	(0.07)	(0.72)		(-1.40)	(0.94)	(0.21)	
IVOL	-0.2635***	-0.2214***	-0.1548**		-0.1141*	-0.2240***	-0.2830***	
	(-4.82)	(-3.57)	(-2.33)		(-1.76)	(-4.03)	(-4.88)	
REV	-0.0043	-0.0035	-0.0080*		-0.0103***	-0.0086**	0.0009	
	(-1.44)	(-0.98)	(-1.84)		(-3.22)	(-2.42)	(0.25)	
PRICE	-0.0014*	-0.0026***	-0.0029***		-0.0026***	-0.0021***	-0.0020**	
	(-1.80)	(-2.91)	(-3.72)		(-3.39)	(-2.76)	(-2.44)	
AG	0.0215	-0.0076	0.0119		-0.0009	0.2578	0.0066	
	(1.47)	(-0.69)	(0.86)		(-0.05)	(1.14)	(0.57)	
cons	0.0202***	0.0205***	0.0241***		0.0223***	0.0205***	0.0169***	
	(4.52)	(4.18)	(4.36)		(4.93)	(4.32)	(3.42)	
Obs.	363,333	291,259	272,809		309,937	308,503	308,961	
Adj R^2	0.073	0.091	0.119		0.091	0.089	0.090	

Table 8: Returns on Bivariate Portfolios of Stocks Sorted by Retail Holdings and ST

At the end of each month, stocks are grouped into three portfolios based on retail holdings (RHLD), and then, within each portfolio, stocks are sorted into decile portfolios based on their ST values. The three RHLD-based groups intersect with the decile ST-based groups to generate 30 equal-weighted (EW) portfolios. The portfolios are rebalanced at the end of the following month. We report the equal-weighted (EW) and value-weighted (VW) FF5 alphas for each ST-sorted decile portfolio. The last rows show the differences in the five-factor alphas between decile 10 (high ST) and decile 1 (low ST). The Newey-West (1987) t-statistics are given in parentheses. The sample period is January 1980 to December 2022.

Panel A. Equal Weighted (EW) Portfolios

	1 Low ST	2	3	4	5	6	7	8	9	10 High ST	High-Low
Low RHLD	1.148***	1.241***	1.031***	1.013***	0.951***	0.901***	0.924***	0.783**	0.816**	0.707*	-0.441**
	(3.76)	(4.29)	(4.13)	(4.08)	(3.93)	(3.63)	(3.82)	(2.96)	(2.95)	(2.21)	(-2.89)
Med RHLD	1.214***	1.255***	1.058***	0.999***	0.919***	0.941***	0.886***	0.835***	0.640*	0.558	-0.656***
	(4.32)	(5.04)	(4.38)	(4.53)	(4.08)	(4.35)	(3.66)	(3.43)	(2.29)	(1.71)	(-3.84)
High RHLD	1.227***	1.175***	1.152***	0.942***	0.905***	0.781***	0.839***	0.707**	0.380	0.171	-1.057***
	(4.95)	(4.92)	(5.05)	(4.41)	(4.17)	(3.47)	(3.70)	(3.00)	(1.42)	(0.57)	(-5.55)
AVG	1.196***	1.223***	1.080***	0.985***	0.925***	0.874***	0.883***	0.775**	0.6117*	0.478	-0.718***
	(3.99)	(5.07)	(5.01)	(5.02)	(4.77)	(4.33)	(4.19)	(3.61)	(2.44)	(1.57)	(-5.39)

Panel B. Value Weighted (VW) Portfolios

	1 Low ST	2	3	4	5	6	7	8	9	10 High ST	High-Low
Low RHLD	1.097***	1.192***	1.040***	1.031***	0.959***	0.890***	0.920***	0.782**	0.822**	0.735*	-0.362*
	(3.61)	(4.18)	(4.21)	(4.21)	(4.05)	(3.66)	(3.88)	(2.99)	(2.99)	(2.31)	(-2.29)
Med RHLD	1.201***	1.238***	1.049***	0.991***	0.911***	0.917***	0.870***	0.811***	0.692*	0.559	-0.643***
	(4.33)	(5.10)	(4.48)	(4.57)	(4.16)	(4.31)	(3.72)	(3.37)	(2.50)	(1.71)	(-3.64)
High RHLD	1.185***	1.160***	1.106***	0.930***	0.879***	0.755***	0.811***	0.695**	0.362	0.198	-0.987***
	(4.72)	(4.88)	(4.95)	(4.42)	(4.12)	(3.39)	(3.64)	(2.94)	(1.35)	(0.64)	(-4.95)
AVG	1.161***	1.1968***	1.065***	0.984***	0.916***	0.854***	0.866***	0.763***	0.625*	0.497	-0.664***
	(3.82)	(4.92)	(4.97)	(5.07)	(4.78)	(4.26)	(4.15)	(3.56)	(2.45)	(1.60)	(-4.73)

Table 9: Fama-MacBeth regressions: Salience and Retail Holdings

This table reports the results of a Fama-MacBeth analysis of the impact of retail investors on the relation between a stock's salience theory value and future return. Monthly cross-sectional regressions are run on excess stock returns in month t + 1 on a firm's ST value and interaction terms between ST and retail holdings (RHLD) constructed at the previous month t. The Newey-West (1987) t-statistics are given in parentheses. The sample period is January 1980 to December 2022.

Variables	(1)	(2)
ST	-0.0984***	-0.0749***
	(-7.57)	(-4.35)
ST×RHLD	-0.0048***	-0.0041***
	(-2.94)	(-2.22)
RHLD	-0.0031***	-0.0034***
	(-1.97)	(-2.05)
BETA	0.0004	0.0008
	(0.33)	(0.75)
SIZE	-0.0005	-0.0004
	(-1.65)	(-1.27)
BM	0.0028***	0.0019**
	(2.74)	(2.05)
MOM	0.0061***	0.0071***
	(4.60)	(5.59)
ILLIQ		0.0087
		(0.92)
MAX		0.0003
		(0.02)
IVOL		-0.2183***
		(-5.42)
REV		-0.0026
		(-0.81)
PRICE		-0.0023***
		(-3.29)
AG		0.0169***
		(2.98)
Cons	0.0107***	0.0199***
	(2.89)	(4.50)
Obs	927,401	927,401
Adj R^2	0.057	0.072

Table 10. Fama-MacBeth Regressions: ST Effect with different levels of Retail Holdings.

This table reports the estimated coefficients of the Fama-Macbeth regressions of the monthly expected stock returns on ST values and other control variables under different retail holdings (RHLD) levels. We partition the sample periods into three groups based on retail holding (RHLD). These tercile RHLD-based groups are denoted as low, medium, and High retail holding levels. This table reports the ST effect on different attention levels. The Newey-West (1987) t-statistics are given in parentheses. The sample period is January 1980 to December 2022.

	Low RHLD	Med RHLD	High RHLD	Chow Test
Variables	(1)	(2)	(3)	(4)
ST	-0.0978***	-0.0723***	-0.0645***	F-stat=5.16
	(-3.90)	(-3.28)	(-2.93)	P value= 0.0231
BETA	0.0001	0.0006	0.0013	
	(0.05)	(0.51)	(1.20)	
SIZE	-0.0004	-0.0001	-0.0009***	
	(-0.94)	(-0.44)	(-2.74)	
BM	0.0000	0.0013	0.0034***	
	(0.01)	(1.26)	(3.41)	
MOM	0.0073***	0.0051***	0.0086***	
	(4.62)	(3.15)	(6.98)	
ILLIQ	-0.4280**	-0.0400	0.0054	
	(-2.51)	(-0.82)	(0.57)	
MAX	0.0284	-0.0069	-0.0097	
	(1.41)	(-0.38)	(-0.51)	
IVOL	-0.1877***	-0.2024***	-0.2708***	
	(-3.12)	(-3.67)	(-4.75)	
REV	-0.0078**	-0.0051	-0.0025	
	(-2.07)	(-1.43)	(-0.81)	
PRICE	-0.0031***	-0.0025***	-0.0014	
	(-3.80)	(-3.59)	(-1.59)	
AG	0.0144*	0.0242**	0.0034	
	(1.65)	(2.27)	(0.19)	
Cons	0.0217***	0.0188***	0.0177***	
	(4.57)	(4.68)	(4.83)	
Obs.	309,307	309,133	308,961	
Adj R^2	0.095	0.087	0.080	

Table 11: Bivariate portfolios of stocks sorted by Social Interaction and ST

At the end of each month, stocks are grouped into three portfolios based on social interaction proxies. Then, stocks are sorted into decile portfolios within each portfolio based on their ST values. The three attention-based groups intersect with the decile ST-based groups to generate 30 value-weighted (VW) portfolios. The portfolios are rebalanced at the end of the following month. The last columns show the differences in monthly returns and five-factor alphas between decile 10 (high ST) and decile 1 (low ST). The social interaction proxies- the Facebook Social Connectedness Index (SCIH) in Panel A and Population Density (PD) in Panel B. The Newey-West (1987) t-statistics are given in parentheses. The sample period is January 1980 to December 2022.

Panel A. Double-sorted on SCIH (Facebook Social Connectedness Index) and ST

	EW portfolios				VW portfolios			
ST	Low	Medium	High	AVG	Low	Medium	High	AVG
Low ST	1.312***	1.183***	1.170***	1.222***	1.265***	1.134***	1.151***	1.184***
	(4.52)	(4.06)	(4.37)	(4.06)	(4.33)	(3.87)	(4.28)	(3.86)
2	1.285***	1.171***	1.180***	1.212***	1.271***	1.133***	1.164***	1.189***
	(4.85)	(4.51)	(4.82)	(5.09)	(4.80)	(4.41)	(4.81)	(4.93)
3	1.025***	1.084***	1.102***	1.070***	1.032***	1.063***	1.079***	1.057***
	(4.26)	(4.15)	(4.77)	(4.90)	(4.37)	(4.13)	(4.72)	(4.82)
4	1.046***	0.950***	1.019***	1.004***	1.049***	0.928***	1.011***	0.996***
	(4.65)	(4.02)	(4.74)	(5.15)	(4.72)	(3.94)	(4.71)	(5.06)
5	0.971***	0.980***	0.853***	0.934***	0.989***	0.964***	0.828***	0.927***
	(4.20)	(4.23)	(3.92)	(4.81)	(4.34)	(4.22)	(3.84)	(4.75)
6	0.855***	0.862***	0.868***	0.862***	0.865***	0.835***	0.846***	0.848***
	(3.64)	(3.75)	(3.90)	(4.16)	(3.77)	(3.67)	(3.84)	(4.09)
7	0.889***	0.845***	0.773**	0.836***	0.865***	0.811***	0.758**	0.811***
	(3.65)	(3.42)	(3.29)	(4.00)	(3.58)	(3.34)	(3.24)	(3.87)
8	0.875**	0.868***	0.816***	0.853***	0.917***	0.846***	0.807***	0.857***
	(3.23)	(3.39)	(3.44)	(3.82)	(3.41)	(3.33)	(3.42)	(3.81)
9	0.654*	0.482	0.627*	0.587*	0.696*	0.509	0.641**	0.615**
	(2.19)	(1.77)	(2.57)	(2.39)	(2.32)	(1.85)	(2.63)	(2.45)
High ST	0.546	0.351	0.419	0.439	0.582	0.390	0.453	0.475
	(1.65)	(1.08)	(1.54)	(1.56)	(1.73)	(1.19)	(1.64)	(1.62)
High-Low	-0.766***	-0.832***	-0.751***	-0.783***	-0.684***	-0.745***	-0.698***	-0.708***
	(-4.05)	(-5.39)	(-4.34)	(-5.90)	(-3.59)	(-4.60)	(-3.92)	(-5.17)

Table 11 (continued)

Panel B. Double-sorted on PD (Population density) and ST.

	EW portfolios				VW portfolios			
ST	Low	Medium	High	AVG	Low	Medium	High	AVG
Low ST	1.174***	1.287***	1.240***	1.233***	1.141***	1.250***	1.197***	1.196***
	(4.21)	(4.49)	(4.54)	(4.10)	(4.04)	(4.35)	(4.37)	(3.91)
2	1.147***	1.251***	1.196***	1.198***	1.108***	1.233***	1.166***	1.169***
	(4.64)	(4.88)	(4.51)	(4.97)	(4.51)	(4.84)	(4.45)	(4.79)
3	1.058***	1.034***	1.063***	1.052***	1.039***	1.030***	1.045***	1.0379***
	(4.47)	(4.20)	(4.29)	(4.90)	(4.40)	(4.24)	(4.31)	(4.80)
4	1.080***	1.083***	0.910***	1.025***	1.076***	1.047***	0.918***	1.013***
	(5.08)	(4.88)	(3.94)	(5.15)	(5.08)	(4.76)	(4.04)	(5.10)
5	0.884***	0.916***	1.017***	0.939***	0.890***	0.901***	1.005***	0.932***
	(3.77)	(3.92)	(4.50)	(4.85)	(3.84)	(3.96)	(4.52)	(4.79)
6	0.876***	0.889***	0.823***	0.863***	0.856***	0.875***	0.814***	0.848***
	(3.84)	(3.95)	(3.51)	(4.24)	(3.76)	(3.97)	(3.55)	(4.16)
7	0.780***	0.942***	0.849***	0.857***	0.779***	0.920***	0.834***	0.845***
	(3.35)	(3.83)	(3.65)	(4.03)	(3.34)	(3.80)	(3.68)	(3.97)
8	0.776**	0.824**	0.816***	0.805***	0.762**	0.835**	0.822***	0.806**
	(3.21)	(3.16)	(3.34)	(3.71)	(3.15)	(3.24)	(3.40)	(3.67)
9	0.519*	0.724*	0.653*	0.632*	0.534*	0.742*	0.673*	0.649*
	(2.02)	(2.47)	(2.41)	(2.54)	(2.08)	(2.52)	(2.49)	(2.55)
High ST	0.384	0.568	0.353	0.435	0.446	0.609	0.371	0.475
	(1.34)	(1.77)	(1.09)	(1.48)	(1.53)	(1.88)	(1.14)	(1.55)
High-Low	-0.790***	-0.719***	-0.887***	-0.799***	-0.694***	-0.642***	-0.826***	-0.720***
	(-4.53)	(-3.90)	(-5.09)	(-5.86)	(-3.89)	(-3.52)	(-4.50)	(-5.10)

Table 12: Fama-MacBeth regressions: Salience and Social interaction

This table reports the results of a Fama-MacBeth analysis of the impact of social interaction on the relation between a stock's salience theory value and future return. Monthly cross-sectional regressions are runs of excess stock returns in month t + 1 on a firm's ST value and interaction terms between ST and social interaction proxies (SOCIAL) constructed at the previous month t's end. The social interaction proxies (SOCIAL) are the Facebook Social Connectedness Index (SCIH) and Population Density (PD). The Newey-West (1987) t-statistics are given in parentheses. The sample period is January 1980 to December 2022.

Variables	SCIH (1)	PD (2)
ST	-0.1006***	-0.0752***
	(-5.89)	(-4.38)
ST × SCIH	-0.0010*	
	(-1.96)	
ST × PD		-0.0010*
		(-1.91)
SOCIAL	-0.0004	-0.0000
	(-1.25)	(-0.45)
RHLD	0.0030***	-0.0035**
	(33.74)	(-2.14)
BETA	0.0007	0.0008
	(0.64)	(0.76)
SIZE	-0.0003	-0.0003
	(-1.01)	(-1.18)
BM	0.0015*	0.0019**
	(1.72)	(2.09)
MOM	0.0047***	0.0071***
	(3.70)	(5.59)
ILLIQ	0.0002	0.0077
	(0.02)	(0.81)
MAX	-0.0016	-0.0002
	(-0.12)	(-0.01)
IVOL	-0.1813***	-0.2214***
	(-4.52)	(-5.47)
REV	-0.0064**	-0.0043
	(-2.19)	(-1.57)
PRICE	-0.0020***	-0.0023***
	(-3.09)	(-3.26)
AG	0.0172***	0.0166***
	(3.06)	(2.91)
Cons	0.0188***	0.0199***
	(5.21)	(4.49)
Obs	927,401	927,401
Adj R^2	0.077	0.073

Table 13. Fama-MacBeth Regressions: ST Effect with social interaction levels.

This table reports the estimated coefficients of the Fama-Macbeth regressions of the monthly expected stock returns on ST values and other control variables under different social interaction levels. We partition the sample periods into three groups based on the respective social interaction proxies. These tercile social interaction-based groups are denoted as low, medium, and High social interaction levels. The social interaction proxies (SOCIAL) are the Facebook Social Connectedness Index (SCIH) and Population Density (PD). The Newey-West (1987) t-statistics are given in parentheses. The sample period is January 1980 to December 2022.

	Low SCIH	Med SCIH	High SCIH	Chow Test	Low PD	Med PD	High PD	Chow Test
Variables	(1)	(2)	(3)		(1)	(2)	(3)	
ST	-0.0795***	-0.0899***	-0.0877***	F-stat=7.41	-0.1063***	-0.0515**	-0.0914***	F-stat=7.34
	(-3.63)	(-4.20)	(-3.57)	P value= 0.0065	(-4.49)	(-2.49)	(-3.87)	P value= 0.0067
RHLD	-0.0049**	-0.0019	-0.0047**		-0.0029	-0.0032	-0.0028	
	(-2.56)	(-1.06)	(-2.18)		(-1.44)	(-1.59)	(-1.58)	
BETA	0.0006	0.0003	0.0012		0.0012	0.0007	0.0003	
	(0.56)	(0.24)	(1.08)		(1.02)	(0.57)	(0.31)	
SIZE	0.0001	-0.0005	-0.0004		-0.0003	-0.0002	-0.0005	
	(0.38)	(-1.45)	(-1.34)		(-0.85)	(-0.71)	(-1.55)	
BM	0.0017	0.0017*	0.0024**		0.0023**	0.0015	0.0019*	
	(1.46)	(1.79)	(2.49)		(2.25)	(1.40)	(1.91)	
MOM	0.0070***	0.0064***	0.0074***		0.0066***	0.0078***	0.0070***	
	(5.76)	(3.95)	(5.01)		(4.56)	(5.91)	(4.72)	
ILLIQ	0.0158	0.0215	0.0088		0.0160	-0.0018	0.0188	
	(0.93)	(1.49)	(0.73)		(1.45)	(-0.09)	(1.42)	
MAX	0.0138	-0.0059	0.0062		0.0207	-0.0237	0.0139	
	(0.74)	(-0.32)	(0.30)		(0.98)	(-1.27)	(0.74)	
IVOL	-0.2665***	-0.2300***	-0.2235***		-0.2626***	-0.1555***	-0.2841***	
	(-5.09)	(-4.04)	(-3.57)		(-4.06)	(-2.89)	(-4.85)	
REV	-0.0014	-0.0104***	-0.0056		-0.0045	-0.0042	-0.0080**	
	(-0.45)	(-2.85)	(-1.58)		(-1.35)	(-1.15)	(-2.37)	
ROE	-0.0034***	-0.0019**	-0.0020***		-0.0022**	-0.0027***	-0.0017**	
	(-4.16)	(-2.33)	(-2.59)		(-2.57)	(-3.28)	(-2.40)	
AG	-0.0102	0.0187	0.0025		0.0225	0.0125	0.0211*	
	(-0.63)	(1.13)	(0.17)		(1.10)	(1.07)	(1.67)	
Cons	0.0222***	0.0191***	0.0195***		0.0178***	0.0212***	0.0195***	
	(4.74)	(4.15)	(3.93)		(3.68)	(4.49)	(4.17)	
Obs	312,831	308,152	306,418		311,410	314,224	301,767	
Adj R^2	0.086	0.090	0.091		0.090	0.089	0.090	

Table 14. Fama-MacBeth Regressions: The ST effect in different uncertainty periods

This table reports the estimated coefficients of the Fama-Macbeth regressions of expected stock returns on ST values and other control variables following periods of high and low uncertainty (EPU) in Panel A and ambiguity (QIN) periods in Panel B. The high EPU (low EPU) months are denoted as periods when the Economic policy uncertainty (EPU) is above (below) the median value for the sample period. The high QIN (low) is defined as the periods when the Qindex (QIN) is above (below) the median value for the sample period. Panel A reports the ST effect on different EPU periods, and Panel B presents the ST effect on different ambiguity levels (QIN). The Newey-West (1987) t-statistics are given in parentheses.

	Panel A. EPU			Panel B. QIN		
	Low	High	Chow Test	Low	High	Chow Test
Variables	(1)	(2)		(1)	(2)	
ST	-0.0503**	-0.1014***	F-stat=16.15	-0.0783**	-0.0674*	F-stat=14.24
	(-2.18)	(-3.95)	P value= 0.0001	(-2.25)	(-1.86)	P value= 0.0002
BETA	0.0000	0.0018		0.0000	0.0003	
	(0.03)	(1.00)		(0.00)	(0.15)	
SIZE	-0.0003	-0.0001		-0.0004	0.0003	
	(-0.70)	(-0.29)		(-1.02)	(0.56)	
BM	0.0011	0.0027**		-0.0002	0.0018	
	(0.85)	(2.06)		(-0.18)	(0.79)	
MOM	0.0081***	0.0059***		0.0028	0.0022	
	(6.07)	(2.74)		(1.03)	(0.99)	
ILLIQ	0.0088	-0.0031		0.0026	0.0007	
	(0.79)	(-0.19)		(0.17)	(0.02)	
MAX	0.0189	-0.0176		0.0211	0.0114	
	(1.02)	(-0.83)		(0.85)	(0.34)	
IVOL	-0.2271***	-0.2152***		-0.2102***	-0.1025	
	(-4.32)	(-3.50)		(-2.86)	(-1.14)	
REV	-0.0011	-0.0086**		-0.0084	-0.0009	
	(-0.33)	(-2.02)		(-1.57)	(-0.17)	
PRICE	-0.0014	-0.0027***		-0.0009	-0.0032**	
	(-1.55)	(-2.84)		(-0.90)	(-2.50)	
AG	0.0132*	0.0205**		0.0285**	0.0193	
	(1.69)	(2.54)		(2.45)	(1.33)	
Cons.	0.0158***	0.0169***		0.0120**	0.0206***	
	(3.69)	(3.34)		(2.30)	(2.79)	
Obs.	482,384	445,017		281,605	258,216	
Adj R^2	0.055	0.080		0.064	0.084	

Appendix 1. Definition of Variables

Variable	**Definition**	**Author**
BETA	The stock market slope coefficient is estimated using monthly returns over the past 60 months, if available, or a minimum of 24 months.	Fama and French (1992)
SIZE	Natural log of the firm's market capitalization at the end of month *t*	Fama and French (1992)
BM	The book value ratio to market value at the end of the last fiscal year.	Fama and French (1992)
MOM	The cumulative return from months *t-12* to *t-2*	Jegadeesh and Titman (1993)
REV	Short term reversal-Return on the stock in month *t-1*	Jegadeesh (1990) and Lehmann (1990).
MAX	The maximum daily return within a month	Bali et al. (2011)
IVOL	The standard deviation of the return residuals from a regression of excess daily returns of stock on the CRSP value-weighted index and the daily size and book-to-market factors of Fama and French (1993)	Ang et al. (2009)
ILLIQ	Amihud illiquidity - The average absolute daily return divided by the daily trading volume over the past month	Amihud (2002)
PRICE	Log of closing stock price	Brandt et al. (2010)
AG	The annual growth rate of total assets	Hou et al. (2015)