Echo Chambers in a Social Finance Platform and Option-Implied Moments of Stock Performance

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Abstract

This thesis examines the role of echo chamber in financial markets. Using measures built by Cookson et. al. (2022) and variables based on option prices (DeMiguel et. al. (2013)), I analyzed how selective exposure shapes investors' perceptions of implied risks and expected excess stock returns. The results highlight that increased disagreement expressed by users stimulates trading activity, in line with Cookson et. al. (2022). Next, I document that a greater dispersion in the messages a member receives leads to a higher probability of extreme payoffs; higher implied skewness, volatility and expected returns. The analysis shows that the investors' tendency to interact with information that confirms their pre-existing beliefs, creates a polarised environment that biases users' trading decisions and market stability in the short run.

Keywords: Echo Chambers, Financial Markets, Implied Moments, Expected Returns.

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Sumário

Esta tese examina o papel da câmara de eco nos mercados financeiros. Usando medidas construídas por Cookson et. al. (2022) e variáveis baseadas em preços de opções (DeMiguel et. al. (2013)), analisei como a exposição selectiva molda as percepções dos investidores sobre os riscos implícitos e o excesso de retorno esperado das acções. Os resultados destacam que o aumento da discordância expressa pelos utilizadores estimula a atividade de negociação, em linha com Cookson et. al. (2022). Em seguida, documento que uma maior dispersão nas mensagens que um membro recebe leva a uma maior probabilidade de payoffs extremos; maior assimetria implícita, volatilidade e retornos esperados. A análise mostra que a tendência dos investidores para interagir com informações que confirmam as suas crenças pré-existentes cria um ambiente polarizado que enviesa as decisões de negociação dos utilizadores e a estabilidade do mercado a curto prazo.

Palavras-chave: Câmaras De Eco, Mercados Financeiros, Momentos Implícitos, Retornos Esperados.

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1. Introduction

Echo chambers is a growing topic of interest in the analysis of human behavior, especially in societies where digital communication is widespread. The phenomenon identifies news environments in which individuals voluntarily expose themselves to information that confirms their pre-existing beliefs, while reducing critical comparison. In other words, this is a mechanism of self-selecting information that amplifies the risk of falling into cognitive biases, such as confirmation bias[1]. This behavior can influence the ability to evaluate complex situations, leading to a distorted view of reality.

Selective information, already studied in politics and social media, has now also implications in financial markets. The evolution of digital technologies has deeply changed the way investors access information. The nearly unlimited availability of online records has provided traders with a wide range of data on securities, investment strategies and market analysis. In this context, they may only focus on sources that support their financial decisions, ignoring risks and alternative solutions. Selective exposure can lead investors to over- or underestimate several market factors, with negative consequences on their investment decisions. At systemic level, if a large number of traders base their choices on biased and homogeneous statements, price mismatches, unexpected volatility and speculative bubbles may arise, affecting the efficiency of the market.

Moreover, this behavior is often amplified by social network algorithms, which aim to maximize user engagement. One example is StockTwits, a platform where members discuss opinions and strategies about financial securities. A study by Cookson et al. (2022)[2] found that optimistic investors (bulls) are more likely to follow other bulls while avoiding interactions with pessimistic users (bears). These dynamic fuels a cycle of mutual confirmation that limits opportunities for comparison and contributes to market volatility. In addition, these cognitive biases can result in non-optimal portfolio choices, characterized by a lack of diversification or a tendency to follow market trends without critical analysis.

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[1] Confirmation bias is a cognitive bias that leads people to seek information that confirms their pre-existing beliefs, while ignoring conflicting ones.

[2] Cookson, J. Anthony, et al. "Echo Chambers." The Review of Financial Studies, vol. 36, no. 2, Aug. 2022.

Understanding how this phenomenon influences investor behaviour can help develop strategies to mitigate the consequences of information siloing, improve expectations setting and ensure greater efficiency of the system. In order to do that, I first replicated the results of 'Echo Chambers' paper to assess the effects of selective information on turnover and cumulative abnormal returns (CARs). Next, I extended the analysis using options market data to better understand trader's attitude. I used these inputs because of their ability to represent investors' expectations through implied moments, including implied volatility, implied skewness and excess returns. The first two measures, directly obtained from option prices, provide information regarding the distribution of projected profits and the perception of future exposures. On the other hand, excess returns represent the required premium for perceived risk. It allows us to assess whether and how investors adjust their expectations based on the disagreement and uncertainty they received. Unlike standard models, which consider only variance, implied moments capture higher-order risk features, such as the probability of extreme market swings.

The variables taken from the work of Cookson et al. (2022), include measures to analyze the relationships between platform users. One of these is the disagreement in the mean of the messages received by the member, 'Received Disagreement'. It represents the diversity of sentiments an investor gets in his feed. The second key measure, 'Received Uncertainty', is the average standard deviation of the opinions a user is exposed to, which quantifies the variability of the information received. 'Sender Disagreement' is the standard deviation of feelings ('bullish' if optimistic or 'bearish' if pessimistic) expressed on that stock-day. It captures the dispersion of opinions between platform users.
Implied skewness and volatility are used to estimate the distribution of expected returns and the perception of future fluctuations. This helps us to understand how investors assess risk and the way these measures are influenced by the information they get on the platform. Finally, cumulative abnormal returns capture the deviations from market expectations, providing a direct measure for the effect of echo chambers on users' trading choices.

To avoid selective exposure being affected by other variables, the analysis employs a multiple regression approach. This method allows to consider time and stock fixed effects, thus eliminating potential biases coming from macroeconomic conditions. The results achieved, reveal a significant impact of echo chambers on both investors' behaviour and their perception of risk. It emerges that an increase in disagreement expressed by the StockTwits users is related to higher trading activity. The finding suggests that greater divergence stimulates individuals to review their opinions, thereby fueling stock exchanges. However, with more dispersion of sentiment in the messages received, transaction volumes appear to decrease. In this case, we can say that investors are more cautious when there are mixed emotions.

Regarding risk expectations, research results indicate that implied skewness significantly increases as received disagreement rises. This means that, in a market characterized by different opinions among traders, one expects a higher probability of extreme returns, both positive and negative. In other words, the increase in implied skewness reflects an environment in which participants perceive higher risks, which can lead to significant losses or gains.

A similar effect is also observed for implied volatility, which grows as disagreement becomes more pronounced. This is a sign that, in the presence of divergent opinions, investors expect greater uncertainty about future price directions. Conversely, cumulative abnormal returns have a negative effect on return expectations. Meaning that after periods of exceptional performances, traders are likely to revise their forecasts, taking a more realistic view towards expected risks. By reducing enthusiasm and the formation of speculative bubbles, this dynamic can normalize markets. The results on generalized lower bounds illustrate that the disagreement and uncertainty received from users slightly increases expected returns. This reveals how echo chambers influence investors' valuations, highlighting its impact on risk and return perspectives.

The last paragraph shows that Sender Disagreement, measured at day *t*, and the information siloing variables, Received Disagreement and Received Uncertainty, significantly influence the future level of Sender Disagreement (t + x) over a three-month horizon. The analysis, in this case, suggests that selective exposure have meaningful consequences for the persistence of disagreement.

The results clearly illustrate that echo chambers is not just a theoretical or isolated phenomenon but have concrete consequences on both investor behaviour and market efficiency in the short term. The users' tendency to seek and interact with information that confirms their pre-existing beliefs creates a polarised environment that biases investors' trading decisions and market stability.

The thesis proceeds as follows. Section 2 presents a review of the existing literature, providing a theoretical framework covering the main papers on echo chambers and its effect on traders' expectations. There are also studies on expected returns, implied skewness and volatility, focusing on how these measures influence the performance of market participants. The third section describes the data, variables and methodologies used to conduct the empirical analysis. Section 4 presents the results obtained and discusses their effects on investor behaviour and market efficiency. The last chapter concludes my thesis by a summary of the findings. It also suggests hints for future research, such as extending the analysis to other geographical contexts, different time horizons or studying interventions to reduce selective exposure in financial markets.

2. Literature review

The literature studying echo chambers has increased the understanding of investor behaviour in financial markets. It shows how selective exposure, by creating highly polarised environments, can reduce openness to different perspectives and negatively influence investment decisions.

A paper written by Cookson et al. (2022) illustrates this phenomenon in the financial sector. The researchers analyzed the behavior of 400,000 users on StockTwits platform, discovering that optimistic investors (bulls) are more likely to follow other optimistic investors rather than pessimistic ones (bears). This selective exposure to information has an impact on what users see in their newsfeed. According to the study, in a 50-day window, bulls view on average 62 more optimistic posts than bears. Therefore, echo chambers have consequences on the market. This phenomenon leads to higher trading volume and poorer investor performance, because decisions are based on a distorted view of reality.
These results are confirmed by Gentzkow and Shapiro's (2011) research. Looking at selective exposure in political context, they find that people are likely to consume news that confirms their political beliefs. Furthermore, Barber and Odean (2008) show that individual investors, by focusing on a few securities mentioned in the news, engage in incomplete information with negative effects on financial performance. On the contrary, institutional portfolio managers, using better strategies and resources, are not as influenced by disclosures. Their findings show that individual investors usually buy on days when there is more focus on that stock, while professionals sell. Another paper written by Hong and Stein (2007) attempts to explain three phenomena observed in financial markets: price under-reaction in the short term, momentum trading and over-reaction in the long term. In order to do that, the authors identify two types of

individuals: newswatchers and momentum traders. The former represent those who do not interpret price signals, slowing down the spread of information and causing price under-reaction. The latter, on the other hand, try to profit from price trends. Their behaviour triggers price adjustment in the short term, but generates over-reaction in the long run by pushing prices above their fundamental.

Echo chambers, by shaping investors' opinions in financial markets, have also consequences on their ability to predict future returns. Traditionally, have been used models that only include variance to calculate expected payoffs. However, recent studies have shown that this approach is unable to capture the difficulty of today's markets. To get more accurate estimates, we have to consider the entire risk distribution, including measures such as skewness and kurtosis. In particular, the first parameter makes it possible to assess the probability of extreme events, positive or negative, with an impact on future returns. In a selective exposure environment, market agents may underestimate or overestimate the risks related to specific assets, with consequences for the accuracy of forecasts. Therefore, the use of more comprehensive models is crucial to mitigate the effects of echo chambers and improve the quality of investment decisions.

Chabi-Yo, Dim, and Vilkov (2021), looking at the entire risk-neutral distribution of returns, develop a model that uses option prices to get expected yields. By including moments such as skewness in their analyses, researchers improve the predictive power of future returns and provide a broader view of market risk. Their approach goes beyond models based simply on variance, providing investors with better tools to understand financial dynamics. Martin (2017), for example, relying on the implied variance of options, provides a lower bound for expected returns, without considering the risks associated with unexpected events (sudden crises or market corrections). Although this is a useful approach, its ability to capture the overall risk present in volatile markets is limited.
Other papers (Kadan and Tang (2020), Schneider and Trojani (2019)) confirm the importance of extending such analysis. Kadan and Tang (2020) considering a forward-looking perspective and risk-neutral moments, calculate the lower bound of expected stock returns. Using the Negative Correlation Condition (NCC), the authors show that they can apply this methodology to about 80% of the securities in the S&P500 from 2000 to 2016. The results indicate that the lower bound is able to predict future earnings over 3 to 6 months' time horizons. In other words, the use of implied variance alone can lead to an underestimation of risks, especially in case of

volatile markets. These papers highlight the importance to account for multiple factors, such as skewness, to predict returns and mitigate the negative consequences of echo chambers in the financial context.

Rehman and Vilkov (2012), using real-time option data, show that implied skewness is positively correlated with future stock earnings. More precisely, a positive skewness leads to a favorable price adjustment, as a result, securities with positive skewness tend to perform better in the short run. This phenomenon is due to the measures' ability to capture investors' perceptions about over- or undervaluation of stocks. Their results contradict what is presented by Boyer, Mitton and Vorkink (2010), who reveal a negative relationship between historical skewness and expected returns. In other words, a negative skewness observed in the past is associated with higher future payoffs. What Rehman and Vilkov (2012) say is also confirmed by Conrad, Dittmar, and Ghysels (2009). In their article they show that anticipated performances, based on implied skewness, are more accurate than those relying on historical data. The main reason lies in the fact that option markets, being linked to investors' expectations, have direct consequences on future returns. According to the authors, the measure provides real-time traders' opinions and sentiment about risks and earnings, which makes it the best proxy to predict forward market movements.

Xing, Zhang, and Zhao (2010) highlight the importance of using the 'volatility smile'[3] when estimating expected payoffs. They demonstrate that stocks with steeper volatility smiles, which indicate negative skewness, tend to perform worse in subsequent months. According to the authors, a negative skewness indicates a higher probability of extreme events, which can penalize stock performance. Consequently, the volatility smile not only provides relevant information on perceived risk, but also about return expectations in the short term.

The literature on echo chambers, expected returns and risk-neutral skewness provides a theoretical framework for studying investor behaviour and financial markets. Therefore, combining these three areas of research can be useful to identify strategies which might reduce

[3] The graph shape known as 'volatility smile' results from plotting the strike price and implied volatility of a series of options with the same underlying asset and expiration date. An option's implied volatility increases if the underlying asset is farther out of the money (OTM) or in the money (ITM) than it is at the money (ATM). Not all options exhibit the volatility smile.

the negative impact of selective exposure, deepen the analysis on investor decisions and improve market efficiency.

3. Data

This section describes the variables used in the analysis, providing an overview of the information collected and their main characteristics. The data include measures of disagreement and uncertainty, implied skewness and volatility, cumulative abnormal returns, turnover and expected returns. These inputs allow me to study how selective exposure and risk expectations influence investor behaviour and financial performance.

The first one, "Permno", represents the unique identifier for each stock considered. The dataset contains a total of 502,265 observations with 1,078 different securities. Such a large amount of information provides a strong basis for drawing reliable and statistically significant conclusions. The variable "Date" includes a time span ranging from 01/01/2013 to 30/06/2020. This seven-year period collects a variety of relevant economic events, allowing me to study how stocks have reacted to different market environments and the way investors have managed situations of uncertainty and volatility.

3.1 Echo Chambers data

The main explanatory variables used to carry out my research are based on the paper written by Cookson et al. (2022). Their dataset is composed of information taken directly from a social network called StockTwits. This app is used by investors to share opinions about stocks and financial securities. On the platform, subscribers can classify their posts as 'bullish' or 'bearish' to indicate their positive or negative view on a certain asset. This function helps to track members' behaviour and enables researchers to observe how investors are exposed to information. With the platform's data, the authors can analyse the effects of echo chambers on traders' behaviour. It allows them, for example, to link the discussion topics' to users' risk perceptions and investment decisions.

The first variable considered is Sender Disagreement$_{s,t}$[4] (s_disagree$_{s,t}$). This captures the dispersion of opinions between users about stock *s* on day *t*. Sender Disagreement$_{s,t}$ is calculated as the standard deviation of sentiment ('bullish' if optimistic or 'bearish' if pessimistic) expressed on that stock-day.

$$\text{Sender Disagreement}_{s,t} = \frac{1}{N_{s,t} - 1} \sum_{i=1}^{N_{s,t}} \left(\text{Sent}_{i,s,t} - \overline{\text{Sent}}_{s,t}\right)^2$$

Where $N_{s,t}$ is the number of posts about security *s* on date *t*, $\text{Sent}_{i,s,t}$ represents the sentiment of different subscribers and $\overline{\text{Sent}}_{s,t}$ is the average of the previous variable. For example, if all investors were bullish on a given stock, Sender Disagreement$_{s,t}$ would have a low standard deviation (no different opinions). On the contrary, a high standard deviation value indicates a variety of sentiments, which means different opinions among users.

Received disagreement$_{s,t}$ (r_disagree$_{s,t}$) quantifies the level of disagreement in the mean of the messages a member receives from his followers.

$$\text{Received disagreement}_{s,t} = \sqrt{\frac{1}{K_{s,t} - 1} \sum_{i=1}^{K_{s,t}} \left(\hat{\mu}_{i,s,t} - \hat{\mu}_{s,t}\right)^2}$$

$K_{s,t}$ is the number of newsfeeds in which stock *s* appears at date *t* and $\hat{\mu}_{i,s,t}$ ¿ is the average user sentiment about that security. If the subscriber gets posts with different opinions than what is published on average (e.g. many bullish posts and few bearish ones in a bearish market environment), the variable will have a higher value, indicating more disagreement.

Received uncertainty$_{s,t}$ (r_uncertainty$_{s,t}$) measures the dispersion of sentiment in the messages a user receives. It is calculated as the simple mean of the different opinions across subscribers.

$$\text{Received uncertainty}_{s,t} = \frac{1}{K_{s,t}} \sum_{i=1}^{K_{s,t}} \tilde{A}_{i,s,t}$$

[4] Cookson, J. A. and M. Niessner (2020, February). Why don't we agree? Evidence from a social network of investors. Journal of Finance 75 (1), 173 3 228.

Where $K_{s,t}$ is the number of newsfeeds in which stock *s* appears at date *t* and $\hat{\sigma}_{i,s,t}$ is the standard deviation of the dispersion of feelings show to member *i* about security *s* on day *t*. A high value of received uncertainty indicates that the user gets mixed sentiment (bullish and bearish) for a given stock. Conversely, a low value denotes a larger exposure to uniform opinions.

$Hi\_bull_{s,t}$ is a dummy for trading days with an above-median number of bullish statements. The median is calculated considering all days used in the dataset, providing a benchmark of the level of optimism shown on the platform. The variable equals 1 if the message about stock s at date *t* is bullish and 0 otherwise. This makes it possible to classify trading days based on the sentiment expressed by users, in order to analyse the effect of opinions on market dynamics.

3.2 Implied Skewness and Volatility

The data contain model-free implied skewness (MFIS) and model-free implied variance (MFIV) of log returns[5] based on Rehman and Vilkov's (2012) paper. The term 'model-free' indicates that these variables were created directly from the option prices observed in the market, without making assumptions about return distributions. In this way, we can generate measures derived solely from the available data, thus increasing the reliability of the estimates.

The implied volatility represents the expected variance of a stock's future earnings. The researchers used the options prices between 10 and 180 days to construct it. In particular, they did not consider deep-in-the-money options and options with zero open interest, to reduce the influence of the early exercise premium. However, the data available in the market do not provide volatility values for all possible combinations of strike price and expiration. Therefore, the authors estimated the missing values to get a continuous representation of the implied volatility curve. The variables Mfiv30 and Mfiv60 measure implied volatility with 30 and 60 days to maturity. Table 1 shows that both have positive and rather high means and standard

[5] MFIS and MFIV are derived in Bakshi, Kapadia, and Madan (RFS, 2003) article. The authors have studied skewness in financial systems, focusing on individual security and market index options. In the research, the skewness of single returns is decomposed into systematic and idiosyncratic components, showing how these aspects are related to option price variation. Using empirical analyses, the researchers show that the risk-neutral distributions of individual securities are less negatively skewed than those of the market index.

deviations, suggesting that the market anticipates high volatility over the time horizon considered.

The implied skewness denotes the skewness of the expected return distribution. To calculate it, is used a strategy similar to the previous one. The authors got information from option prices on a given stock, considering options with different levels of moneyness[6]. Unlike traditional estimates, which only use two volatility smile points (such as at-the-money and out-of-the-money options), MFIS considers information from all available options. This makes it more accurate in capturing market expectations. Implied skewness is computed as the weighted average of option price moments. The mean values for Mfis30 and Mfis60 (table 1) are negative (-0.2709 and -0.3027 respectively), implying that the market is likely to expect bearish movements in stock prices.

3.3 Cumulative Abnormal Returns

The variable Abnormal returns$_{s,t}$ represents daily abnormal returns of stock *s* on date *t*. This measure is derived by calculating the difference between the actual return of the stock on day *t* and the expected yield based on a reference model, the CAPM. The abnormal returns were retrieved from CRSP[7], in stocks and financial instruments section (Stock / Security Files, U.S. Daily Event Study). The use of this variable helps to study how company news or announcements cause deviations from market forecasts. Therefore, abnormal returns allow me to investigate the influence of information dynamics on users' behavior.

Cumulative Abnormal Returns$_{s,(t-5 \text{ to } t-1)}$[8] and Cum. Abnormal Returns$_{s,(t-30 \text{ to } t-6)}$ are the cumulative abnormal returns in the days preceding date *t*. The variables are constructed by summing the abnormal returns downloaded from CRSP. With an average of 0.0136, Cum. Abnormal Returns$_{s,(t-5 \text{ to } t-1)}$ shows that securities usually generate positive earnings five days

[6] Ratio of strike to share price.

[7] The Center for Research in Security Prices (CRSP) is a collection of security price, return, and volume data for the NYSE, AMEX and NASDAQ stock markets.

[8] I used as Risk model the Market-Adjusted Model. Estimation Parameters are Estimation Window (days) 81009, Minimum Number of Valid Returns (observations) 8709, Gap (days) 8509, Event Window Start (days) 8-59 and Event Window End (days) 8-19.

before t. The percentiles indicate that while 10% of stocks have negative returns (p10 = -0.0475), 90% enjoy positive abnormal profits (p90 = 0.1296). However, when considering a longer horizon, the average Cum. Abnormal Returns$_{s,(t-30\ to\ t-6)}$ is negative. The standard deviation, which is higher than the previous case, reflects greater variability of abnormal returns.

Cum. Abnormal Returns$_{s,(t+1\ to\ t+5)}$[9], Cum. Abnormal Returns $_{s,(t+1\ to\ t+10)}$ e Cum. Abnormal Returns$_{s,(t+1\ to\ t+30)}$ measure the cumulative abnormal returns in the days following date t. These variables are constructed in line with the previous ones. As we can see from table 1, the standard deviation increases with the time horizon (0.3092 for Cum. Abnormal Returns$_{s,(t+1\ to\ t+30)}$). As a result, some stocks benefit from abnormal gains while others suffer losses. The percentiles show that the market is more volatile over a longer period.

The variable Volatility$_{s,(t-5\ to\ t-1)}$ represents the standard deviation of abnormal returns calculated during the five days before date t. In this case, the 90th percentile (0.0956) suggests that, for some assets, the variance of abnormal returns is higher close to the date considered. This could indicate a greater investor perception of risk towards the stock. The variable provides insight into how recent volatility influences the behaviour of market participants.

3.4 Turnover

Abnormal Log Turnover$_{s,t}$ is computed as the difference between log turnover on day t[10] and the average log turnover from t - *140* to t - *20* trading days[11]. In this way, the measure is standardized against a historical mean and deviations caused by news or changes in market sentiment are eliminated. The standard deviation (1.0671) and the percentiles indicate changes

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[9] I used as Risk model the Market-Adjusted Model. Estimation Parameters are Estimation Window (days) 81009, Minimum Number of Valid Returns (observations) 8709, Gap (days) 8509, Event Window Start (days) 8+19 and Event Window End (days) 8+59.

[10] Log turnover on day t is the natural logarithm of turnover on day t. The turnover was calculated as the ratio of Volume (vol) and Number of Shares Outstanding (shrout). Volume (vol) and Number of Shares Outstanding (shrout) were retrieved from CRSP, Stock / Security Files, Daily Stock Files.

[11] Average log turnover from t - *140* to t - *20* trading days is the average log turnover over a six-month horizon, skipping most recent days.

in the trading volumes observed on day *t*. Some securities show a decrease in turnover whereas others experience considerable increases.

The variable Abnormal log $turnover_{s,t-1}$, represents Abnormal Logarithmic Turnover of stock *s* on the previous day (*t 3 1)*. The measure is used to compare the turnover of two consecutive days to check whether the variations observed on *t* are the result of isolated events or market trends. The results in Table 1 show consistency between the two estimates.

3.5 Generalized Bounds

The variables Glb2_D30 and Glb3_D30 provide generalized lower bounds on conditional expected excess (simple) returns for individual stocks in the S&P500[12]. To calculate GLB, the authors derived market risk parameters (such as beta, volatility and skewness) for each security. These inputs are used to define the set of possible values for », a key measure when computing expected excess returns. Given that the data available in the market do not provide all strike prices, the authors have to estimate the missing values. Therefore, they used a technique called Hermite's interpolation. In simple words, given the implied volatility for an option with a certain strike price, we can calculate the volatility for another option with a slightly different price. This allows to make implied volatility values when data are not available. Glb2_D30 is computed assuming relative risk aversion of 2 and half prudence of 1[13] (or temperance of 4[14] for Glb3_D30) at 30 days to maturity. These variables are better than the ones based just on variance, as they include higher moments of the distribution (such as skewness and kurtosis) leading to a more accurate estimate of expected excess returns. Glb3_D30 has a higher average than Glb2_D30 (0.1195), implying that, with more conservative parameters, the bounds are even higher.

[12] Chabi-Yo, Fousseni and Dim, Chukwuma and Vilkov, Grigory, "Generalized Bounds on the Conditional Expected Excess Return on Individual Stocks" 2020.

[13] Based on the second-order Taylor series expansion.

[14] Based on the third-order Taylor series expansion.

3.6 Limitations of variables used

The variables used in the analysis provide a detailed insight into the dynamics of disagreement, uncertainty and market reactions, but have some limitations that could influence the final results and the interpretation of the emerging evidence. Measures such as Sender Disagreement$_{s,t}$, Received disagreement$_{s,t}$ and Received Uncertainty$_{s,t}$ depend on the availability of data collected from StockTwits. Although the social platform is a great source of information, its users may not accurately represent the market sentiment. Furthermore, regarding volatility and skewness variables, the use of interpolations to overcome the lack of data is an additional source of uncertainty. The estimates might reduce the reliability of risk measures, by skewing their ability to reflect investors' expectations. In high volatility periods, the use of approximations might amplify valuation errors. Turnovers and abnormal returns, calculated on a reference period, could also be affected by exceptional market events, such as financial crises or unexpected news. These situations could bias the data, and generate outputs that do not reflect long-term trends. Finally, the autocorrelation among the variables employed may result in an overestimation of correlations between disagreement, uncertainty and investor behaviour, thus reducing the robustness of the findings. This phenomenon increases the chances of incorrectly attributing causality to spurious correlations, making it more complex to distinguish each variable's independent effects.

These limitations lead to consider the estimates obtained with caution. Although my research allows me to study investor behaviour and market dynamics, the problems highlighted in the data and methodologies call for further analysis to confirm the results.

4. Regression Analysis

After the description and analysis of the variables involved in my research, in this section, I want to discover how information spreads through echo chambers. Suppose first that individuals follow other users regardless of their sentiment. In this way, we expect each subscriber's feed to reflect the general feeling of the market, providing a uniform distribution of the opinions published. Conversely, individuals who decide to enter the information siloing will be more likely to see messages that misrepresent the overall distribution of sentiment, amplifying the risk of creating a distorted view of the market.

In their paper, Cookson et al. (2022) estimated the level of selective exposure in StockTwits data. Under the assumption that the connections between users are randomized by the combination of messages published (bullish or bearish) and the number of posts received, they calculated the probability that the opinions seen at member-stock-day level have the same sentiment. According to the theory, in an environment without echo chambers, the impressions received by each subscriber should be proportional to the overall distribution of sentiment in the platform. When comparing the theoretical probability with the observed one, they found that information siloing results in significant selective exposure. In other words, the chance of receiving messages that confirm our ideas is higher than the one predicted by a randomized distribution. Therefore, the findings show that users are more likely to engage with people who share similar thoughts.

4.1 Information siloing on Abnormal Log Turnover

Using regression models, I try to understand the effect of echo chambers on trading volumes in the market and the system's ability to correctly reflect the intrinsic stock value. As a first step, I study how selective exposure shapes abnormal log stock turnover and cumulative abnormal returns (CARs).

To perform this analysis, I estimate the effect of information siloing using variables such as market sentiment, dispersion of opinions and the degree of uncertainty received by investors.

$$(1)\ \text{Abnormal Log Turnover}_{s,t} = \beta_1\,\text{Sender Disagreement}_{s,t} + \beta_2\,\text{Received Disagreement}_{s,t} + \beta_3\,\text{Received Uncertainty}_{s,t} + X'_{s,t}\,\delta + \eta_t + \gamma_{s,m(t)} + \varepsilon_{s,t}$$

where Abnormal Log Turnover$_{s,t}$ is the abnormal logarithmic turnover of stock *s* on date *t*, and $X_{s,t}$ are control variables. Like Cookson et al. (2022), I also included in the regression day (η_t) and stock-month ($\gamma_{s,m(t)}$) fixed effects. In this case, I focus on the two coefficients β_2 and β_3. The former measures how increasing perceived disagreement (greater diversity in messages received across users indicates greater selective exposure) is associated with turnover. If echo chambers create information siloing that disadvantages trading, we expect a positive value for β_2 ($\beta_2 > 0$). The coefficient β_3 analyses how increasing received uncertainty (a greater variety of messages seen by users implies less selective exposure) is associated with abnormal stock turnover. In this case, we forecast a negative value for β_3 ($\beta_3 < 0$). Table 2 presents the equation's (1) results.

In the first regression (column (1)) Abnormal Log Turnover$_{s,t}$ is the dependent variable and Sender Disagreement$_{s,t}$ the independent one. The control variables are: Abnormal Log Turnover$_{s,t-1}$, Volatility$_{s,(t-5 \text{ to } t-1)}$, Cum. Abnormal Returns$_{s,(t-5 \text{ to } t-1)}$ and Cum. Abnormal Returns$_{s,(t-30 \text{ to } t-6)}$. Sender Disagreement$_{s,t}$ has a positive (0.138) and significant ($p < 0.01$) coefficient. The finding implies that increased uncertainty across investors could lead to a rise in trading activity. Within the control variables Abnormal Log Turnover$_{s,t-1}$ shows a positive effect (0.309) on turnover, while Cum. Abnormal Returns$_{s,(t-30 \text{ to } t-6)}$ has a negative output (-0.078).

In column (2) Received Disagreement$_{s,t}$ is added. In this case, greater dispersion in messages received from users represents higher disagreement in the information set. The introduction of a second independent variable reduces the impact of Sender Disagreement$_{s,t}$ (from 0.138 to 0.022). Unlike Cookson et al. (2022), here the coefficient on Received Disagreement$_{s,t}$ is bigger than the one on Sender Disagreement$_{s,t}$. The R-squared improves (0.725), meaning that this specification explains better the variance than the previous column.

In the third regression (3) Received Uncertainty$_{s,t}$ and Sender Disagreement$_{s,t}$ are used as independent variables. In this case, Received Uncertainty$_{s,t}$ has a negative and statistically significant coefficient ($\beta_3 = -0.138$). This implies that, we observe more turnover when selective exposure to information reduces the dispersion of sentiment received by users.

In column (4), there are three independent variables: Sender Disagreement$_{s,t}$, Received Disagreement$_{s,t}$ and Received Uncertainty$_{s,t}$. While the first two have positive and significant estimates, β_3 is negative (-0.188). Thus, an increase in uncertainty leads to a lower trading activity. In the last specification, the independent variables are the same as in (4). Here, there is only Abnormal Log Turnover$_{s,t-1}$ as control variable. Although the outputs are very similar to the previous ones, the R^2 goes up, reaching a value of 0.732.

The results observed are consistent with the 'Echo Chambers' paper, however, my coefficients have much higher values. This may be due to the different number of observations considered and the fact that my data were not standardized. Unlike Cookson et al. (2022), in my case a one standard deviation increase in Sender Disagreement$_{s,t}$ raises abnormal turnover by 13.39% of its mean.

The next step is to analyze how information siloing relates to abnormal returns. For this, I run a test in which measures of disagreement and selective exposure interact with an indicator of above median sentiment ($Hi\_bull_{s,t}$).

$$\text{(2) Cum. Abnormal Returns}_{s,(t+1 \text{ to } t+5)} = \beta_1 \, Hi\_bull_{s,t} + X'_{s,t}\,\delta + \eta_t + \gamma_{s,m(t)} + \varepsilon_{s,t}$$

As in previous regression, I include day (η_t) and stock-month ($\gamma_{s,m(t)}$) fixed effects. All specifications have Abnormal Returns$_{s,t}$, Volatility$_{s,(t-5 \text{ to } t-1)}$, Cum. Abnormal Returns$_{s,(t-5 \text{ to } t-1)}$ and Cum. Abnormal Returns$_{s,(t-30 \text{ to } t-6)}$ as control variables ($X_{s,t}$). The first column only considers $Hi\_bull_{s,t}$ as independent measure. In the other three tests, besides Sender Disagreement$_{s,t}$, Received Disagreement$_{s,t}$ and Received Uncertainty$_{s,t}$, there are three parameters describing the interaction between the measures of disagreement and the indicator for stock-days with above median bullishness ($Hi\_bull_{s,t}$ x $s\_disagree_{s,t}$, $Hi\_bull_{s,t}$ x $r\_disagree_{s,t}$, $Hi\_bull_{s,t}$ x $r\_uncertainty_{s,t}$). Results are presented in table 3.

The data show that $Hi\_bull_{s,t}$ has a low but positive impact on the dependent variables. Consequently, with optimistic beliefs, future returns are likely to increase over different time horizons. On the contrary, in the 'Echo Chambers' paper, the above median StockTwits sentiment has a negative effect on cumulative abnormal returns through 30 days. Like the results of the previous regression, this may be due to the different number of observations considered and data standardization.

The dispersion of opinions among users (Sender Disagreement$_{s,t}$) has a positive impact on CARs, meaning that investors may see profit opportunities when there is more disagreement in the market. The negative coefficient of the relationship between $Hi\_bull_{s,t}$ e Sender Disagreement$_{s,t}$ shows that greater dispersion in messages published can dampen subscribers' optimism. A similar result is observed for Received Disagreement$_{s,t}$. Probably, analysts' uncertainties trigger caution among traders, making the market less reactive. In contrast, the positive interaction among $Hi\_bull_{s,t}$ e Received Uncertainty$_{s,t}$ suggests that, when sentiment is bullish, increased uncertainty may amplify expected performances. In an optimistic environment, investors might view insecurity as a profit opportunity. These findings are in line with those pointed out by Cookson and the other researchers, even though the numbers and significance levels are quite different.

The control variables (Abnormal Returns$_{s,t}$, Cum. Abnormal Returns$_{s,(t-5 \text{ to } t-1)}$ and Cum. Abnormal Returns$_{s,(t-30 \text{ to } t-6)}$) exhibit negative and significant coefficients in all specifications. It indicates that past abnormal returns are inversely related to future CARs.

Finally, the R^2 rises progressively to 0.845. The inclusion of independent parameters and the extension of the time horizon make the model increasingly explanatory. The higher value in the last column, implies that market expectations have a greater effect on long-term payoffs.

In conclusion, the regression results highlight the favorable impact of the platform sentiment on future cumulative abnormal returns. This consequence, however, may be limited or amplified by the levels of disagreement and uncertainty.

4.2 Information siloing on implied moments

The paragraph analyses the effect of information siloing on expected excess returns, implied skewness and volatility. The aim is to study how users' perceived disagreement and uncertainty influence their behavior, risk perception and assessment of future profits in the short run.

After evaluating the impact of echo chambers on abnormal stock turnover, I now look at the consequences of this bias on implied skewness. To examine this relationship, I use a regression model that links Mfis30 to the measures of received disagreement and uncertainty among subscribers.

$$(3)\quad \text{Mfis30}_{s,t} = \beta_1 \text{ Sender Disagreement}_{s,t} + \beta_2 \text{ Received Disagreement}_{s,t} + \beta_3 \text{ Received Uncertainty}_{s,t} + X'_{s,t}\,\delta + \eta_t + \gamma_{s,m(t)} + \varepsilon_{s,t}$$

Table 4 shows the results obtained. The only difference between this equation and (1), lies in the dependent variable. The independent variables, control variables and fixed effects are the same as in table 2. In all specifications, Sender Disagreement$_{s,t}$ has a positive and significant coefficient. The finding suggests that more divergence among analysts leads to higher skewness in future performance expectations.

The control measures Abnormal Log Turnover$_{s,t-1}$ e Volatility$_{s,(t-5 \text{ to } t-1)}$ have a positive and significant outcome in all regressions. When past returns have been positive, investors might hold unbalanced upward views. In the same way, increased market uncertainty may lead people to hedge against extreme shocks, inducing greater implied skewness. The other two control variables, however, have negative coefficients. Indicating that, after positive earnings, the market is likely to stabilize, dampening any expectation of change.

The inclusion of Received $\text{Uncertainty}_{s,t}$ in columns (3), (4) and (5), does not change $\text{Mfis30}_{s,t}$. Maybe, users do not get the dispersion of sentiment in the messages as a powerful signal to modify their opinions. In contrast, Received $\text{Disagreement}_{s,t}$ presents a significant value in two out of three specifications. Showing that disagreement leads to a more skewed returns estimate.

Table 5 results illustrate how measures of divergence and uncertainty influence implied market volatility. These outputs are derived following the same regression as in the previous case, in terms of independent variables, control variables and fixed effects. The only difference concerns the dependent variable, $\text{Mfiv30}_{s,t}$.

The coefficient of Sender $\text{Disagreement}_{s,t}$, while low, has a positive and significant value in two out of five specifications. Meaning that, when general divergence among investors rises, volatility is likely to increase as well. The result is intuitive: risk perception is higher in a market with different opinions. The variable that quantifies the level of disagreement in the mean of the messages a user receives has a positive and significant effect. In other words, risk awareness is amplified when subscribers get mixed sentiments. In contrast, Received $\text{Uncertainty}_{s,t}$ presents a significant impact (at 5%) only in column (4). This suggests that a greater dispersion of feelings in the messages seen by members could reduce the implied volatility of the market. However, the low value of the coefficient implies that uncertainty have a small consequence on $\text{Mfiv30}_{s,t}$.

Abnormal Log $\text{Turnover}_{s,t-1}$ and $\text{Volatility}_{s,(t-5 \text{ to } t-1)}$ have both a positive and significant effect in all the regressions done. Indeed, it is reasonable that a higher standard deviation of abnormal returns prior to date *t* leads to a larger implied volatility. On the contrary, cumulative abnormal returns have negative coefficients. After periods of sharp rises, investors may consider lower the risk of further changes. The R^2 has a constant value of 0.922, denoting a high explanatory power of the model. The stability of the output means that the variables used are appropriate to capture the variation in implied volatility.

Results confirm that user's disagreement and uncertainty, past earnings, recent volatility and abnormal returns are important factors in shaping investors' expectations and therefore short-term risk perceptions.

To conclude this section, I examine the effect of disagreement and uncertainty variables on the generalized lower bounds on conditional expected excess (simple) returns. The values are obtained following the same specifications as in the previous case, in terms of independent variables, control variables and fixed effects. Here, the dependent variable is $Glb2\_D30_{s,t}$. Table 6 presents the outputs of the regressions.

In the first row, Sender $Disagreement_{s,t}$ has a very small coefficient. We can say that different opinions among investors have a marginal impact on expected returns. On the other hand, Received $Disagreement_{s,t}$ has a significant, but low (0.003) effect in all specifications. The result shows that the level of disagreement perceived by users, moderately increases the dependent variable. The same is true for Received $Uncertainty_{s,t}$. Although the value is small, the statistical significance of 1% suggests that the dispersion in received sentiments could lead to an increase in returns expectations.

Focusing on the control variables, Cum. Abnormal $Returns_{s,(t-5 \text{ to } t-1)}$ and Cum. Abnormal $Returns_{s,(t-30 \text{ to } t-6)}$ are both negative and highly significant in all tests. This means that past earnings can cause a reduction in expected excess returns. Whereas, Abnormal Log $Turnover_{s,t-1}$ e $Volatility_{s,(t-5 \text{ to } t-1)}$ present opposite coefficients and do not show significance in any of the regressions performed. The previous day's abnormal returns and recent volatility have no direct influence on $Glb2\_D30_{s,t}$. It is possible that investors do not consider as relevant these two measures when making future expectations.

To sum up, under different market perspectives, users demand higher returns as a premium for the risk taken. However, short-term CARs seem to reduce these expectations, implying a risk-adjustment process at systemic level.

4.3 The Persistence of Disagreement

The results reported in the previous paragraphs suggest that echo chambers fosters the persistence of disagreement among investors. As a result, it creates information silos that widen the divergences over time. To validate this thesis, like in the 'Echo Chambers' paper, I ran three different tests with the aim of studying the impact that Sender Disagreement (at day *t*) and selective exposure measures, Received Disagreement and Received Uncertainty, have on future Sender Disagreement (at day *t + x*). The analysis covers a time period ranging from one to ninety days following reference day *t*.

$$(4)\quad \text{Sender Disagreement}_{s,(t+x)} = \beta_1 \text{ Sender Disagreement}_{s,t} + \beta_2 \text{ Received Disagreement}_{s,t} + \beta_3 \text{ Received Uncertainty}_{s,t} + \eta_t + \alpha_s + \varepsilon_{s,t}$$

Sender Disagreement$_{s,(t+x)}$ is the dispersion of opinions between users about stock *s* on day *t* + *x*, where *x* is the number of days after day *t*. I also included in the regression day (η_t) and permno (α_s) fixed effects. The standard errors were clustered at security and day level to increase the reliability of estimated coefficients. The outcome values for the three time lags (1 - 30 days, 1 - 60 days, 1 - 90 days) are shown in Figure 1, Figure 2 and Figure 3.
In the first graph, the Received Disagreement estimates appear to be positive immediately after t, meaning that a rise in the variable leads to an increase of future Sender Disagreement. However, as we approach the end of the period considered, the effect becomes smaller and less significant. On the contrary, Received Uncertainty shows a weaker influence, with coefficients frequently close to zero. Therefore, the dispersion of sentiment in the messages a user receives does not contribute to the persistence of future disagreement.
Looking at the 60-day time horizon, Figure 2 shows a more pronounced path than the previous one. This indicates that, while reducing, the effect of disagreement in the messages received can last for almost two months. Figure 3 confirms that the impact of Received Disagreement generally sinks in the long run. In fact, although the variable's coefficient is significant during the first few days, it leans to zero in around 60 days. On the other hand, the Received Uncertainty curve reveals that the variable does not play a relevant role in predicting future Sender Disagreement.

In conclusion, these results are consistent with the ones of Cookson et al. (2022) and imply that echo chambers have meaningful consequences for the persistence of disagreement.

5. Conclusions

The study contributes to the understanding of how information spread through the public, highlighting the key role of echo chambers in shaping investors' decisions in option markets. Information siloing, by facilitating exposure to news that confirms pre-existing beliefs, creates an environment in which the ability to make rational decisions and discuss with different perspectives is compromised. These dynamics are able to influence not only single users, but the general market behaviour. Investment choices, based on a distorted view of reality, can undermine trading volumes and contribute to systematic inefficiencies like the overestimation of expected returns. Furthermore, the lack of interaction with other opinions increases the overall market volatility and jeopardizes long-term stability.

The analysis was conducted through regression models and showed how disagreement and uncertainty in messages received by StockTwits' subscribers can influence key aspects of investor behaviour and market dynamics (such as trading volume, risk perception and expected returns). The results reveal that increased disagreement expressed by users is correlated with higher trading activity. This means that investors generally react to the information they get, without verifying it or looking at its long-term consequences. At the same time, when there is a significant dispersion of sentiment in the messages received, traders become more cautious, thus reducing stock exchanges volume. An inverse dynamic is then evident, greater uncertainty seems to make individuals temporize, avoiding hasty solutions. These opposite reactions highlight how complex the decision-making process is in the presence of echo chambers.
Furthermore, the study was conducted on implied skewness and volatility. It proved that, in a market characterized by a high degree of disagreement among investors, one expects a greater probability of extreme returns and uncertainty regarding future price directions. Information selection has also an effect on cumulative abnormal returns. In this case, after periods of abnormal profits, it appears that traders usually change their forecasts and mature a more realistic view about future risks. Therefore, it seems that in the long run, there are self-correction mechanisms which help the market to stabilize. The analysis on the generalized lower bounds on conditional expected excess (simple) returns reveals that disagreement and uncertainty received from StockTwits users slightly increase expected returns. This indicates how echo chambers shape investors' valuations, highlighting its impact on risk and return forecasts. In the last paragraph of my thesis, I wanted to replicate Cookson et al.'s (2022) discussion regarding the persistence of disagreement. As their paper already pointed out, my research confirms that selective exposure significantly influences the future level of Sender Disagreement. This means that echo chambers create information silos that widen the divergences over time.

However, the use of data taken directly from StockTwits platform, and the interpolation of some variables impose caution when evaluating the results achieved. Although the social network provides useful information regarding member sentiment, these may not fully represent the entire investor population. Furthermore, the need to apply interpolation to fill the gaps in the data may reduce the accuracy of estimated coefficients. I hope that these limitations will be overcome by future research, e.g. by extending the analysis to different contexts. This would be an opportunity to study whether what is observed on StockTwits can be generalized or depends on the application characteristics. Similarly, taking a different time horizon could allow one to consider additional economic periods and shocks. The use of more advanced research methodologies, such as those based on Instrumental Variables, Difference-in-Differences or Machine Learning, could improve the significance of the data and the ability to measure user sentiment. Moreover, integrating information from different sources, like other social networks (X or Instagram), would provide a broader representation of investor behaviour.

The study has also some practical implications. On the one hand, understanding how cognitive biases, such as echo chambers, work can contribute to the creation of social networks that promote greater informational exposure and reduce opinions polarization. Furthermore, the analysis underlines the need for investors to diversify media sources. Relying only on one single news channel or on a small group of users may compromise their ability to assess risks correctly with negative outcomes on investment decisions. Finally, regulators could develop normative actions to improve the efficiency and transparency of the financial system, thus reducing the threat of speculative bubbles.

My thesis is related to the literature discussing the role of information in fostering more conscious trading choices by investors. In an increasingly digitalized environment, gaining access to diversified news sources is essential for market stability. In fact, more opinions exposure would reduce the negative impact of echo chambers. This attitude can lower the chance of making decisions based on incorrect data and improve individuals' confidence in the financial system. It could also mitigate the risk of speculative bubbles and unexpected crises by enhancing the market's ability to allocate resources effectively.

6. Appendix

Table 1: Summary statistics

This table presents summary statistics, on stock-day level, for each variable used in the regressions.

Variable	Observations	Mean	SD	p10	p25	p50	p75	p90
Abnormal Log Turnover$_{s,t}$	412876	.413531	110.267	-.6593755	-.2514435	.2074044	.8432649	1.768.708
Abnormal Log Turnover$_{s,t-1}$	412738	.3219395	1.086.852	-.7278638	-.3168853	.1245269	.7284476	1.629.896
Abnormal Returns$_{s,t}$	391713	.0061428	.0956404	-.0508067	-.0202579	.0008466	.0231026	.0610088
Cum. Ab. Returns$_{s,(t-5 \text{ to } t-1)}$	391778	.0106314	.192031	-.1161675	-.0475382	6.13e-06	.047409	.1295663
Cum. Ab. Returns$_{s,(t-30 \text{ to } t-6)}$	390150	.0149573	.3798261	-.2852251	-.1230456	-.0059898	.1056811	.2964338
Cum. Ab. Returns$_{s,(t+1 \text{ to } t+5)}$	391969	-.0022854	.1543471	-.1181641	-.0518916	-.005312	.0361733	.1042766
Cum. Ab. Returns$_{s,(t+1 \text{ to } t+10)}$	391969	-.0039176	.2120534	-.1717702	-.0768365	-.0081839	.0523493	.1492837
Cum. Ab. Returns$_{s,(t+1 \text{ to } t+30)}$	391969	-.0084457	.3465303	-.3086661	-.1426044	-.016441	.0955643	.2723092
Glb2_D30$_{s,t}$	286797	.0978131	.1603959	.0192931	.0321627	.0556937	.1012019	.1917298
Glb3_D30$_{s,t}$	286822	.0955098	.1599445	.0182082	.0311488	.0543451	.0986347	.1851494
Hi_bull$_{s,t}$	502265	.500447	.5000003	0	0	1	1	1
Mfis30$_{s,t}$	293689	-.2709055	.4959965	-.7826028	-.5403321	-.3029807	-.0552672	.2327149
Mfis60$_{s,t}$	293683	-.3027894	.4333819	-.7781857	-.557954	-.334514	-.0886292	.1878023
Mfiv30$_{s,t}$	293689	.6132248	.6361521	.0628789	.1492717	.4155924	.8942311	1.429.906
Mfiv60$_{s,t}$	293683	.5990092	.5955853	.0645726	.148858	.4122434	.9021677	1.374.521
Received Disagreement$_{s,t}$	429860	.1887369	.2299353	0	0	.0167518	.4045199	.5272841
Received Uncertainty$_{s,t}$	429860	.2941271	.4310359	0	0	.0167933	.5098449	1.028.221
Sender Disagreement$_{s,t}$	429860	.5004611	.4324981	0	0	.5762081	.8944272	1.032.796
Volatility$_{s,(t-5 \text{ to } t-1)}$	391553	.0449844	.0736028	.009111	.0159817	.0287236	.0497136	.0860452

Table 2: Information siloing on Abnormal Log Turnover

This table examines how proxies for selective exposure behavior (received disagreement and received uncertainty), together with sender disagreement, shapes abnormal log stock turnover. Observations are at the stock-day (*s,t*) level. Sender Disagreement$_{s,t}$ captures the dispersion of opinions between users about stock *s* on day *t*. Received disagreement$_{s,t}$ quantifies the level of disagreement in the mean of the messages a member receives from his followers. Received uncertainty$_{s,t}$ measures the dispersion of sentiment in the posts a user receives. Abnormal Log Turnover$_{s,t}$ is computed as the difference between log turnover on day *t* and the average log turnover from *t - 140* to *t - 20* trading days. Control variables are Abnormal log turnover of stock *s* on the previous day (*t 3 1)*; Volatility$_{s,(t-5 \text{ to } t-1)}$, calculated as the standard deviation of abnormal returns during the five days before *t*; and Cumulative abnormal returns, measured over days *t - 30* to *t - 6* and *t - 5* to *t - 1*. I included in the regression day (η_t) and stock-month ($\gamma_{s,m(t)}$) fixed effects. Standard errors (in brackets) are separately clustered by stock and day. *** 1%, ** 5%, * 10% significance level.

	Abnormal Log Turnover$_{s,t}$				
	(1)	(2)	(3)	(4)	(5)
Sender Disagreement$_{s,t}$	0.138***	0.022***	0.231***	0.127***	0.122***
	(0.005)	(0.005)	(0.007)	(0.007)	(0.007)
Abnormal Log Turnover$_{s,t-1}$	0.309***	0.302***	0.308***	0.301***	0.318***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Volatility$_{s,(t-5 \text{ to } t-1)}$	0.041	0.018	0.045	0.020	
	(0.052)	(0.052)	(0.052)	(0.051)	
Cum. Abnormal Returns$_{s,(t-5 \text{ to } t-1)}$	0.108***	0.112***	0.107***	0.111***	
	(0.018)	(0.018)	(0.018)	(0.018)	
Cum. Abnormal Returns$_{s,(t-30 \text{ to } t-6)}$	-0.078***	-0.081***	-0.077***	-0.079***	
	(0.013)	(0.013)	(0.013)	(0.013)	
Received Disagreement$_{s,t}$		0.385***		0.456***	0.443***
		(0.013)		(0.013)	(0.013)
Received Uncertainty$_{s,t}$			-0.138***	-0.188***	-0.187***
			(0.006)	(0.007)	(0.007)
Constant	0.236***	0.226***	0.231***	0.216***	0.214***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
# observations	370,952	370,952	370,952	370,952	405,294
R^2	0.723	0.725	0.724	0.728	0.732
# clusters (days)	1,745	1,745	1,745	1,745	1,745
# clusters (permno)	1,069	1,069	1,069	1,069	1,070
Day FE	Yes	Yes	Yes	Yes	Yes
Month-Stock FE	Yes	Yes	Yes	Yes	Yes

Table 3: Information siloing on Cumulative Abnormal Returns

This table examines how proxies for selective exposure behavior (received disagreement and received uncertainty), together with sender disagreement and an indicator for stock-days with above median bullishness ($Hi\_bull_{s,t}$), shapes daily stock returns. Observations are at the stock-day (*s,t*) level. Sender $Disagreement_{s,t}$ captures the dispersion of opinions between users about stock *s* on day *t*. Received $disagreement_{s,t}$ quantifies the level of disagreement in the mean of the messages a member receives from his followers. Received $uncertainty_{s,t}$ measures the dispersion of sentiment in the posts a user receives. The panel presents equation 1 results, with cumulative abnormal stock returns as dependent variable. Control variables are Abnormal $returns_{s,t}$ of stock *s* on date *t*; $Volatility_{s,(t\text{-}5 \text{ to } t\text{-}1)}$, calculated as the standard deviation of abnormal returns during the five days before *t*; and Cumulative abnormal returns, measured over days *t - 30* to *t - 6* and *t - 5* to *t - 1*. I included in the regression day (η_t) and stock-month ($\gamma_{s,m(t)}$) fixed effects. Standard errors (in brackets) are separately clustered by stock and day. *** 1%, ** 5%, * 10% significance level.

	Cum. Abnormal $Returns_{s,(t+1 \text{ to } \&)}$			
	(1)	(2)	(3)	(4)
	t+5	t+5	t+10	t+30
$Hi\_bull_{s,t}$	0.001*	0.010***	0.012***	0.008***
	(0.001)	(0.002)	(0.002)	(0.002)
Abnormal $Returns_{s,t}$	-0.403***	-0.401***	-0.571***	-0.692***
	(0.016)	(0.017)	(0.016)	(0.015)
$Volatility_{s,(t\text{-}5 \text{ to } t\text{-}1)}$	-0.031	-0.030	-0.040	0.005
	(0.022)	(0.022)	(0.029)	(0.025)
Cum. Abnormal $Returns_{s,(t\text{-}5 \text{ to } t\text{-}1)}$	-0.379***	-0.378***	-0.540***	-0.637***
	(0.013)	(0.013)	(0.012)	(0.012)
Cum. Abnormal $Returns_{s,(t\text{-}30 \text{ to } t\text{-}6)}$	-0.278***	-0.277***	-0.379***	-0.421***
	(0.014)	(0.014)	(0.014)	(0.013)
Sender $Disagreement_{s,t}$		0.009***	0.014***	0.010***
		(0.002)	(0.002)	(0.002)
$Hi\_bull_{s,t}$ x $s\_disagree_{s,t}$		-0.021***	-0.032***	-0.019***
		(0.004)	(0.005)	(0.004)
Received $Disagreement_{s,t}$		-0.003	-0.002	-0.000
		(0.002)	(0.002)	(0.002)
$Hi\_bull_{s,t}$ x $r\_disagree_{s,t}$		-0.016**	-0.031***	-0.038***
		(0.008)	(0.010)	(0.010)
Received $Uncertainty_{s,t}$		0.000	0.000	0.001
		(0.001)	(0.001)	(0.001)
$Hi\_bull_{s,t}$ x $r\_uncertainty_{s,t}$		0.006	0.022***	0.022***
		(0.005)	(0.006)	(0.006)
Constant	0.010***	0.003	0.003	0.002
	(0.001)	(0.002)	(0.002)	(0.003)
# observations	381,189	381,127	381,127	381,127
R^2	0.414	0.414	0.589	0.845
# clusters (days)	1,885	1,885	1,885	1,885
# clusters (permno)	1,072	1,072	1,072	1,072
Day FE	Yes	Yes	Yes	Yes
Month-Stock FE	Yes	Yes	Yes	Yes

Table 4: Information siloing on implied skewness

This table examines how proxies for selective exposure behavior (received disagreement and received uncertainty), together with sender disagreement, shapes implied skewness. Observations are at the stock-day (*s,t*) level. Sender $\text{Disagreement}_{s,t}$ captures the dispersion of opinions between users about stock *s* on day *t*. Received $\text{disagreement}_{s,t}$ quantifies the level of disagreement in the mean of the messages a member receives from his followers. Received $\text{uncertainty}_{s,t}$ measures the dispersion of sentiment in the posts a user receives. $\text{Mfis30}_{s,t}$ denotes the skewness of the expected return distribution. Control variables are Abnormal log turnover of stock *s* on the previous day (*t 3 1)*; $\text{Volatility}_{s,(t-5 \text{ to } t-1)}$, calculated as the standard deviation of abnormal returns during the five days before *t*; and Cumulative abnormal returns, measured over days *t - 30* to *t - 6* and *t - 5* to *t - 1*. I included in the regression day (η_t) and stock-month ($\gamma_{s,m(t)}$) fixed effects. Standard errors (in brackets) are separately clustered by stock and day. *** 1%, ** 5%, * 10% significance level.

	$\text{Mfis30}_{s,t}$				
	(1)	(2)	(3)	(4)	(5)
$\text{Sender Disagreement}_{s,t}$	0.031***	0.028***	0.028***	0.027***	0.028***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
$\text{Abnormal Log Turnover}_{s,t-1}$	0.009***	0.008***	0.009***	0.008***	0.006***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$\text{Volatility}_{s,(t-5 \text{ to } t-1)}$	0.228***	0.227***	0.227***	0.227***	
	(0.043)	(0.043)	(0.043)	(0.043)	
$\text{Cum. Abnormal Returns}_{s,(t-5 \text{ to } t-1)}$	-0.195***	-0.195***	-0.195***	-0.195***	
	(0.016)	(0.016)	(0.016)	(0.016)	
$\text{Cum. Abnormal Returns}_{s,(t-30 \text{ to } t-6)}$	-0.059***	-0.059***	-0.059***	-0.059***	
	(0.012)	(0.012)	(0.012)	(0.012)	
$\text{Received Disagreement}_{s,t}$		0.008*		0.007	0.010**
		(0.005)		(0.005)	(0.004)
$\text{Received Uncertainty}_{s,t}$			0.003	0.003	0.002
			(0.002)	(0.002)	(0.002)
Constant	-0.294***	-0.295***	-0.294***	-0.295***	-0.289***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
# observations	250595	250595	250595	250595	272533
R^2	0.606	0.606	0.606	0.606	0.601
# clusters (days)	1,745	1,745	1,745	1,745	1,745
# clusters (permno)	828	828	828	828	829
Day FE	Yes	Yes	Yes	Yes	Yes
Month-Stock FE	Yes	Yes	Yes	Yes	Yes

Table 5: Information siloing on implied volatility

This table examines how proxies for selective exposure behavior (received disagreement and received uncertainty), together with sender disagreement, shapes implied volatility. Observations are at the stock-day (*s,t*) level. Sender Disagreement$_{s,t}$ captures the dispersion of opinions between users about stock *s* on day *t*. Received disagreement$_{s,t}$ quantifies the level of disagreement in the mean of the messages a member receives from his followers. Received uncertainty$_{s,t}$ measures the dispersion of sentiment in the posts a user receives. Mfiv30$_{s,t}$ represents the expected variance of a stock's future earnings. Control variables are Abnormal log turnover of stock *s* on the previous day (*t 3 1)*; Volatility$_{s,(t-5 \text{ to } t-1)}$, calculated as the standard deviation of abnormal returns during the five days before *t*; and Cumulative abnormal returns, measured over days *t - 30* to *t - 6* and *t - 5* to *t - 1*. I included in the regression day (η_t) and stock-month ($\gamma_{s,m(t)}$) fixed effects. Standard errors (in brackets) are separately clustered by stock and day. *** 1%, ** 5%, * 10% significance level.

	Mfiv30$_{s,t}$				
	(1)	(2)	(3)	(4)	(5)
Sender Disagreement$_{s,t}$	0.003***	-0.002	0.003**	-0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Abnormal Log Turnover$_{s,t-1}$	0.007***	0.006***	0.007***	0.006***	0.010***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Volatility$_{s,(t-5 \text{ to } t-1)}$	0.177***	0.175***	0.177***	0.175***	
	(0.051)	(0.051)	(0.051)	(0.051)	
Cum. Abnormal Returns$_{s,(t-5 \text{ to } t-1)}$	-0.043**	-0.043**	-0.043**	-0.043**	
	(0.020)	(0.020)	(0.020)	(0.020)	
Cum. Abnormal Returns$_{s,(t-30 \text{ to } t-6)}$	-0.051***	-0.051***	-0.051***	-0.051***	
	(0.015)	(0.015)	(0.015)	(0.015)	
Received Disagreement$_{s,t}$		0.015***		0.016***	0.016***
		(0.003)		(0.003)	(0.003)
Received Uncertainty$_{s,t}$			-0.001	-0.002**	-0.002
			(0.001)	(0.001)	(0.001)
Constant	0.597***	0.597***	0.597***	0.596***	0.610***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
# observations	250595	250595	250595	250595	272533
R^2	0.922	0.922	0.922	0.922	0.922
# clusters (days)	1,745	1,745	1,745	1,745	1,745
# clusters (permno)	828	828	828	828	829
Day FE	Yes	Yes	Yes	Yes	Yes
Month-Stock FE	Yes	Yes	Yes	Yes	Yes

Table 6: Information siloing on expected excess returns

This table examines how proxies for selective exposure behavior (received disagreement and received uncertainty), together with sender disagreement, shapes expected excess returns. Observations are at the stock-day (*s,t*) level. Sender Disagreement$_{s,t}$ captures the dispersion of opinions between users about stock *s* on day *t*. Received disagreement$_{s,t}$ quantifies the level of disagreement in the mean of the messages a member receives from his followers. Received uncertainty$_{s,t}$ measures the dispersion of sentiment in the posts a user receives. Glb2_D30$_{s,t}$ provide generalized lower bounds on conditional expected excess (simple) returns for individual stocks in the S&P500. Control variables are Abnormal log turnover of stock *s* on the previous day (*t 3 1)*; Volatility$_{s,(t-5\text{ to }t-1)}$, calculated as the standard deviation of abnormal returns during the five days before *t*; and Cumulative abnormal returns, measured over days *t - 30* to *t - 6* and *t - 5* to *t - 1*. I included in the regression day (η_t) and stock-month ($\gamma_{s,m(t)}$) fixed effects. Standard errors (in brackets) are separately clustered by stock and day. *** 1%, ** 5%, * 10% significance level.

	Glb2_D30$_{s,t}$				
	(1)	(2)	(3)	(4)	(5)
Sender Disagreement$_{s,t}$	0.001**	-0.000	-0.000	-0.001	-0.001*
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Abnormal Log Turnover$_{s,t-1}$	0.001	0.000	0.001	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Volatility$_{s,(t-5\text{ to }t-1)}$	-0.005	-0.006	-0.005	-0.006	
	(0.017)	(0.017)	(0.017)	(0.017)	
Cum. Abnormal Returns$_{s,(t-5\text{ to }t-1)}$	-0.024***	-0.024***	-0.024***	-0.024***	
	(0.009)	(0.009)	(0.009)	(0.009)	
Cum. Abnormal Returns$_{s,(t-30\text{ to }t-6)}$	-0.025***	-0.025***	-0.025***	-0.025***	
	(0.006)	(0.006)	(0.006)	(0.006)	
Received Disagreement$_{s,t}$		0.003***		0.003***	0.003***
		(0.001)		(0.001)	(0.001)
Received Uncertainty$_{s,t}$			0.001***	0.001**	0.001***
			(0.000)	(0.000)	(0.000)
Constant	0.098***	0.098***	0.098***	0.098***	0.098***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)
# observations	250570	250570	250570	250570	272507
R^2	0.891	0.891	0.891	0.891	0.891
# clusters (days)	1,745	1,745	1,745	1,745	1,745
# clusters (permno)	828	828	828	828	829
Day FE	Yes	Yes	Yes	Yes	Yes
Month-Stock FE	Yes	Yes	Yes	Yes	Yes

Figure 1: Persistence of disagreement (1 - 30 days)

The figure shows the impact that Sender Disagreement (at day t) and selective exposure measures, Received Disagreement and Received Uncertainty, have on future Sender Disagreement (at day t + x). The coefficients result from separate regressions (one per day), for days t + 1 to t + 30. I included in the regression day (η_t) and permno (α_s) fixed effects. The standard errors were clustered at security and day level. The vertical bars indicate 95% confidence intervals.

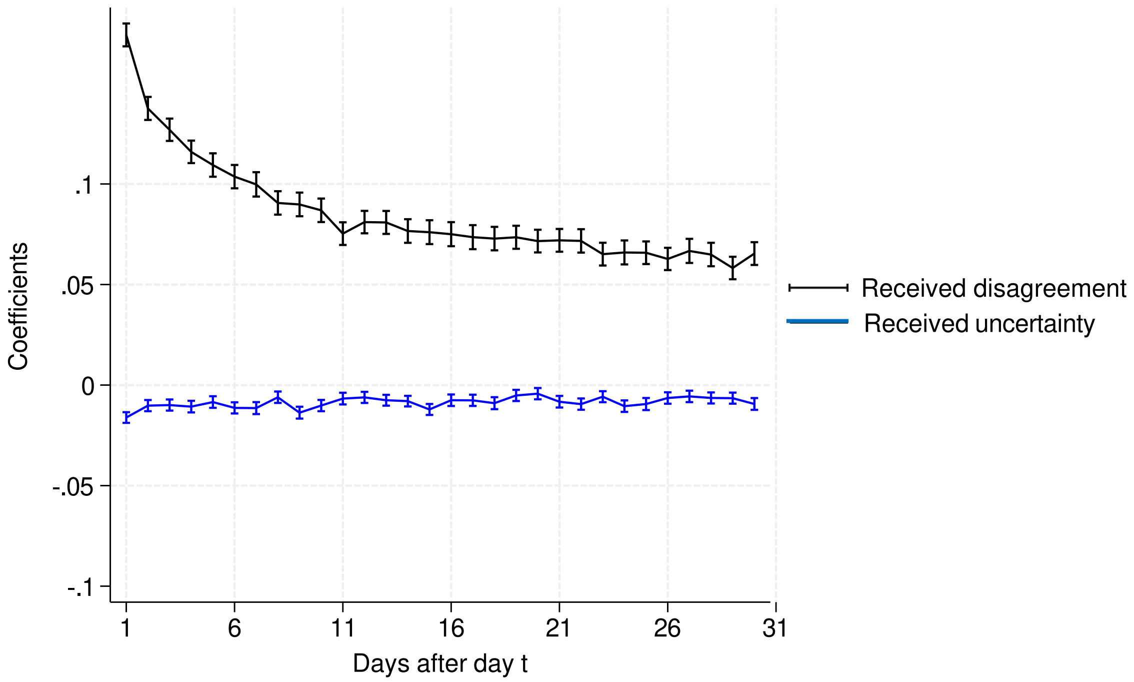


Figure 2: Persistence of disagreement (1 - 60 days)

The figure shows the impact that Sender Disagreement (at day t) and selective exposure measures, Received Disagreement and Received Uncertainty, have on future Sender Disagreement (at day t + x). The coefficients result from separate regressions (one per day), for days t + 1 to t + 60. I included in the regression day (η_t) and permno (α_s) fixed effects. The standard errors were clustered at security and day level. The vertical bars indicate 95% confidence intervals.

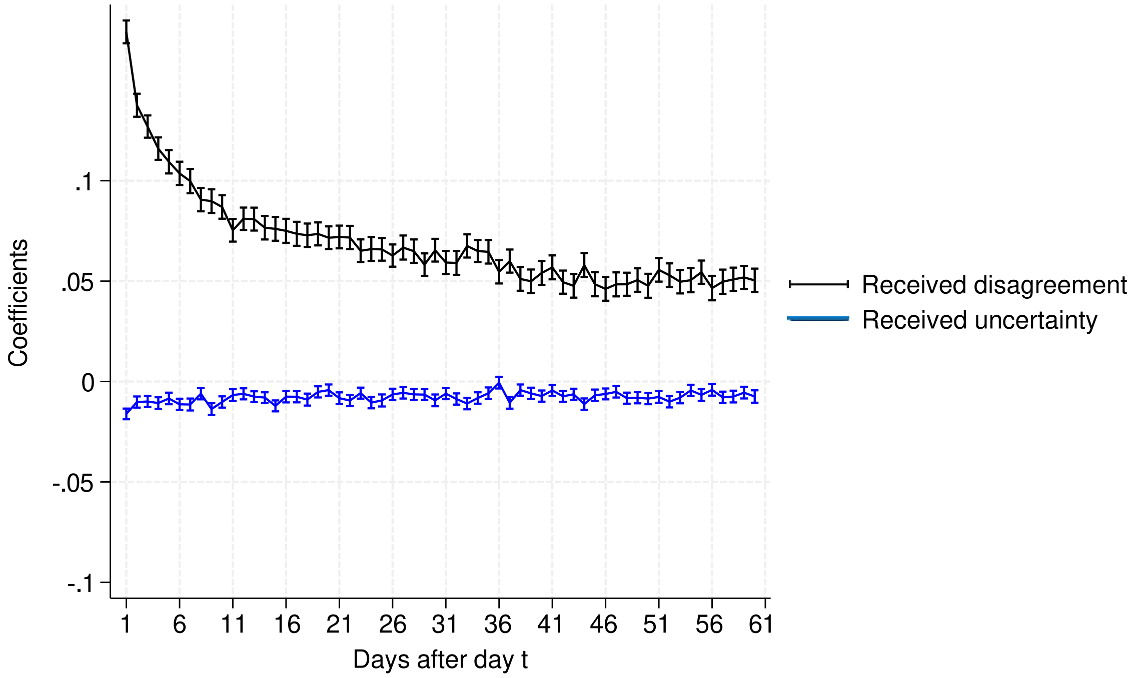
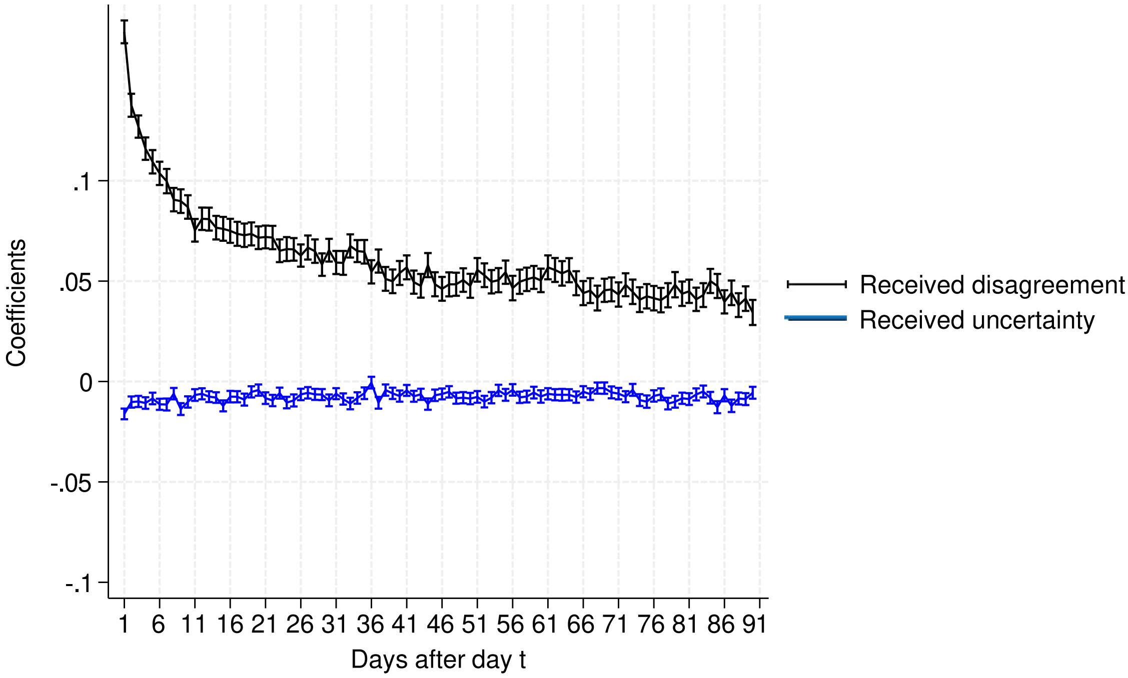


Figure 3: Persistence of disagreement (1 - 90 days)

The figure shows the impact that Sender Disagreement (at day t) and selective exposure measures, Received Disagreement and Received Uncertainty, have on future Sender Disagreement (at day t + x). The coefficients result from separate regressions (one per day), for days t + 1 to t + 90. I included in the regression day (η_t) and permno (α_s) fixed effects. The standard errors were clustered at security and day level. The vertical bars indicate 95% confidence intervals.



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