The Digital Trail of the Main Street and Stock Price Synchronicity

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Abstract

Using a high-frequency dataset of click-level activity from two online websites, we disentangle retail investor market and firm-specific information demand (FSID and MSID). We show that these two dimensions generally act as substitutes, with heightened market uncertainty driving increased MSID and reduced aggregate FSID. When MSID and individual firms' FSID are negatively related, greater (lower) synchronicity (i.e. the degree of comovement) in attention is linked to higher (lower) return synchronicity, consistent with attention crowding-out and firm uncertainty effects. Conversely, when they move in the same direction, we observe an attention spillover mechanism that reduces (increases) return synchronicity by amplifying (reducing) firm-specific signals. We show that both mechanisms coexist and vary by firm characteristics. Using a novel attention jump detection methodology, we further demonstrate our findings.

Keywords: clickstream data, attention allocation, return synchronicity, retail investors, uncertainty

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1 Introduction

The digital age has reshaped the investing landscape, enabling new ways to analyze how investors process information and its impact on market dynamics. Investors' digital footprints on online investing platforms serve as a valuable data source, offering insights into how individuals interact with the vast amount of information available on the internet. In this paper, we leverage such data and provide novel evidence on how investors allocate their attention between firm-specific and market-specific information and how these choices influence the synchronicity of stock returns with the market returns.

Asset price comovement and synchronicity with the market[5] are major topics in asset pricing literature, with implications for portfolio diversification, market efficiency, and price informativeness. Higher synchronicity has been associated with increased price volatility (Morck et al., 2000), reduced idiosyncratic firm-specific price signals (Barberis et al., 2005), and diminished diversification benefits (Kalok and Yue-Cheong, 2014; Huang et al., 2024). Recent evidence indicates that stock return synchronicity has been rising over time (Huang et al., 2024), yet there is little consensus among scholars on the drivers of this trend. Existing studies document competing findings and explanations, suggesting that synchronicity may be caused either by attention shifts to broader market signals (e.g., Peng, 2005; Peng and Xiong, 2006; Veldkamp, 2006; Hellwig and Veldkamp, 2009; Mondria, 2010) or through the rapid incorporation of firm-specific information into prices and the reduction of idiosyncratic volatility (e.g., Dasgupta et al., 2010).

This study seeks to address these conflicting perspectives by analyzing a dataset comprising more than two billion user clicks from two separate investment-related websites. Leveraging this novel dataset, we observe investor interactions with firm-specific (micro-level) and market-specific (macro-level) information in unprecedented detail. By examining how attention allocation shifts during periods of heightened market uncertainty, we provide new insights into the mechanisms driving stock return comovement and synchronicity. In so doing, we contribute to the ongoing debate on whether synchronicity arises from increased firm-specific or market-specific information processing.

We focus specifically on retail investors, whose behavior is captured by our dataset as it reflects information demand on platforms frequently used by this group. These platforms often act as multifunctional tools, enabling screen stocks, create portfolios, and access related news, similar to professional terminals. Retail investors now account approximately one-fifth

[5] In this paper we refer to (a) stock price comovement as the degree of comovement in individual stocks' returns; (b) stock price synchronicity as the synchronicity between a stock's returns with the overall market return.

of the total market trading volume[6], a significant increase that has spurred considerable academic interest in their role in shaping financial markets (Boehmer et al., 2021; Welch, 2022; Schwarz et al., 2022; Barber et al., 2023; Bryzgalova et al., 2023). By concentrating on retail investor attention patterns, we aim to shed light on how their behavior interacts with varying levels of market uncertainty and contributes to key market outcomes.

In particular, we investigate the dynamic relationship between aggregated firm-specific (FSID) and market-specific (MSID) information demand, and research how this allocation evolves under conditions of heightened market uncertainty. Using daily frequency data, we compute the relative emphasis investors place on each category of information and directly demonstrate how these attention patterns change over time. We show that MSID and aggregated FSID mainly act as substitutes, a finding that supports existing models of limited attention and attention capacity constraints (Prat, 1997; Sims, 2003). Due to limited attention, investors cannot process all the information available in the market, and therefore they need to choose which signals to observe. Our analysis shows a negative relationship between MSID and aggregated FSID, supported by correlation analysis and contemporaneous regressions.

The substitutional relationship between the two elevates at times of heightened market uncertainty, as retail investors will divert their focus away from firm-specific information and toward market-wide signals. This behavior aligns with theoretical models suggesting that investors attempt to predict the collective actions of others and mitigate portfolio uncertainty during uncertain periods (Peng, 2005; Peng and Xiong, 2006; Veldkamp, 2006). These results provide an understanding of the role of retail attention allocation in driving stock return synchronicity. Employing the VIX index as a proxy for market-wide uncertainty, we show that it is positively related to MSID and negatively related to aggregated FSID. However, these relationships are based on the aggregated FSID, rather than the information demand for individual firms.

Establishing the negative relationship between MSID and aggregated FSID, as well as their relationship with uncertainty, supports the limited attention theory, but does not provide any insight into the factors causing it. To answer that, we obtain the information demand synchronicity and stock price synchronicity measures (constructed following (Morck et al., 2000)) at a quarterly frequency, for each firm in our sample individually, and examine the separate information demand regimes able to cause price synchronicity. Note that is part of the analysis is different than the one conducted based on the aggregated FSID, as in this part we aim to examin the information demand synchronicity at the individual firm level. Our study is closely related to Drake et al. (2017) who use the R^2 from regressing

[6]https://www.weforum.org/agenda/2023/05/retail-investors-financial-systems-to-accommodate-them/

firm-specific attention on sector and market-wide attention as a measure of comovement, demonstrating how attention impacts asset price comovement. However, R^2 alone cannot determine whether micro and macro information are positively or negatively related, nor can it distinguish the determinants of the observed comovement.

We therefore depart from this strand of literature as we do not only observe the synchronicity measured through the R^2, but also the coefficient between MSID and FSID. We find that when MSID and FSID are negatively related, then information demand synchronicity is positively related to stock price synchronicity, but when they are positively related, a negative relationship between the two holds. This finding provides a robust explanation for the contradiction of whether stock price synchronicity is the effect of more or less firm-specific information incorporated into asset prices (Kalok and Yue-Cheong, 2014). We support that it is mainly caused by more market-specific information being incorporated in asset prices, whereas in all of the regimes identified in this paper, more FSID will cause a lower synchronicity in stock prices.

Existing studies (Sheng and Hirshleifer, 2022; Liu et al., 2022) show that the presence of macroeconomic and firm-specific announcements will crowd out retail investor attention from firm-specific information, as they will increase their focus on market-wide signals. On the contrary institutional investors will increase their firm-specific focus under such circumstances. We argue that both mechanisms co-exist, at least for retail investors, but depend on the firm characteristics. At times of higher uncertainty, retail investors will focus on the market-specific signal, which will (a) crowd out their information demand from firms with higher institutional ownership and higher fundamental's volatility, and (b) create an attention spillover effect to firms owned by more retail investors, and are perceived as safer assets due to their size and book-to-market ratios.

Employing a jump detection methodology following Lee and Mykland (2008) we explore the effect of information demand jumps on stock price synchronicity. By detecting MSID and FSID jumps, we demonstrate the distinct effects of these. We show that positive (negative) jumps in market-wide information demand are linked with a higher (lower) synchronicity of the stock and market returns. Conversely, positive (negative) jumps in firm-specific information demand lead to lower (higher) stock price synchronicity. These results provide empirical support to the theoretical argument that synchronicity manifests when investors allocate their attention to market-wide information and trade multiple assets based on this information. When investors focus on firm-specific information, however, idiosyncratic price movements dominate, reducing synchronicity.

This paper makes several key contributions to the literature. First, we contribute to the debate on whether stock price synchronicity is driven by the incorporation of more or less firm-specific information. On one hand, stock price synchronicity with the market has been linked to investor information processing. In the presence of abundant information, investors face information capacity constraints necessitating the selection of which signals to observe, as they cannot obtain and process all available information. During periods of heightened uncertainty, investors may opt to observe broader signals and use them to trade multiple assets, which can lead to increased stock price comovement and synchronicity of stock returns with market returns (Peng, 2005; Peng and Xiong, 2006; Veldkamp, 2006; Hellwig and Veldkamp, 2009; Mondria, 2010).

However, there is existing literature providing evidence that it may not be the distraction of investors, but rather the rapid incorporation of information in asset prices that drives the observed comovement patterns (Dasgupta et al., 2010; Kalok and Yue-Cheong, 2014). We argue that both of these mechanisms hold and they do not constitute a contradiction. During periods of high market uncertainty retail investors will be distracted and hence allocate more attention to the market-wide signal, which will be reflected in the higher prices' synchronicity. Similarly, investors' tendency to allocate more attention to firm-specific information will signal a higher firm-specific uncertainty and therefore a weaker firm-specific informational environment. This will in turn create a higher focus on firm-specific information and lead to a higher idiosyncrasy in the stocks' returns instead of synchronicity with the market returns, and vice versa.

Second, we address a critical gap in the literature by empirically linking retail information demand synchronicity to stock return synchronicity. Existing studies have produced mixed findings regarding the relationship of these. Drake et al. (2017) use multiple measures of attention comovement[7], and show that the measure exhibiting the lowest comovement, is the one being broadly used as a measure of retail investor attention. Lin et al. (2019) show that distraction events cause higher stock price synchronicity, especially for high retail ownership stocks. We show that retail investor information demand synchronicity positively (negatively) explains stock price synchronicity when MSID and FSID are negatively (positively) related, following the theoretical predictions.

Third, we show that for the same type of investors, the distraction effect and attention enhancement effect can co-exist. More specifically we observe that when MSID and FSID are positively related, a higher focus on the market may have a spillover effect to firm-specific attention, decreasing the synchronicity of the firm's returns with the market returns. As MSID and FSID move less on the same direction, the market-specific signal will dominate guiding a higher synchronicity on the returns.

[7]More specifically, Bloomberg AIA (Israelsen et al., 2017); EDGAR search volume (Drake et al., 2015) as institutional attention measures and Google SVI (Da et al., 2011) as a retail attention measure.

Fourth, we disentangle the effects of positive and negative linkages between micro- and macro-level information demand on stock price synchronicity through introducing information demand jumps as a novel methodological framework to capture market-wide and firm-specific attention jumps. This approach allows us to directly observe the dynamics of these attention allocation jumps, irrespective of the triggering event. By employing this framework, we not only reaffirm that micro and macro-related investor attention act as substitutes (Lin et al., 2019; Sheng and Hirshleifer, 2022; Liu et al., 2022), but we also uncover their complex interplay with other market variables such as uncertainty. To the best of our knowledge, this is the first study to employ a jumps methodology in this context, establishing a new lens through which to understand information demand in financial markets.

Last, we extend the literature on retail investors by examining how they allocate attention and make financial decisions, thus enhancing our understanding of their role in financial markets. The increasing market participation of those investors has led a large body of academics examining the information acquisition processes of these (Da et al., 2011; Sheng and Hirshleifer, 2022; Liu et al., 2022) as well as their market performance (Welch, 2022; Boehmer et al., 2021; Schwarz et al., 2022; Barber et al., 2023) and investment decisions (deHaan et al., 2023; Bryzgalova et al., 2023). We add to this strand of literature through providing new insights on the information processing of these investors and the possible sources of their distraction, which may be linked to their observed performance. Opposed to existing studies suggesting that, due to their inexperience, retail investors are distracted more easily by the presence of macroeconomic news, we show that this is only one part of the story. In such cases, retail investors are distracted from firms with higher institutional ownership, whereas we observe an attention spillover from the market to the firms that are owned by more retail investors. This finding provides novel evidence on the information processing of retail investors.

The rest of the study is organized into four sections. Section 2 provides an overview of the existing related literature. and formulates the theoretical grounding and the testable hypotheses. Section 3 describes the data and methods used in this paper. Section 4 presents the empirical analysis, and Section 5 concludes.

2 Background

2.1 Literature review

Existing literature suggests that due to information capacity constraints, investors are unable to process all the information available (Prat, 1997), leading to rational inattention (Sims, 2003) and choice of attention allocation (Peng, 2005; Peng and Xiong, 2006; Mondria, 2010). Theoretical models of coordination games (Hellwig and Veldkamp, 2009) show that investors have motives to acquire information to predict their peers' actions. Such coordination may induce a comovement in asset prices, as investors will choose to observe the same public signal, and they will further act on it, leading to comovement either between the stock prices or between the stock prices and the market returns (Peng, 2005; Drake et al., 2017; Lin et al., 2019).

The effect of comovement, however, is not only dependent on the information choice of investors, but also differs between different market conditions. Morck et al. (2000) show that emerging economies exhibit higher stock price comovement than developed economies. They link this finding with reduced investor protection in emerging markets. Brockman et al. (2010) extend these findings by linking this outcome to the quantity and quality of information. They show that high (low) information production leads to low (high) stock price comovement. They support that the countercyclical patterns in comovement are more pronounced for emerging markets, and markets with less developed financial markets, with weaker accounting and transparency standards. Dang et al. (2015) extend this strand of literature, showing that the institutional environment explains the comovement difference between emerging and developed countries. More specifically, they associate the institutional environment of a country with the firm-level information production which in turn, supports the lower price synchronicity in developed countries. Gaganis et al. (2025) show that comovement is higher in more secretive societies, as the idiosyncratic volatility is lower. They further link this finding with investors' information-seeking behaviors and informed trading.

Focusing on the asset prices, existing literature has provided evidence of how style investing and analysts' activity impacts their comovement. Barberis and Shleifer (2003) show that the categorization of assets in styles leads to a high comovement of the assets in the same style. Chan and Hameed (2006) focus on emerging markets and show that the higher number of analysts covering a firm is linked to higher synchronicity of the asset return with the market. They suggest that this is caused by a higher incorporation of market-wide information and a smaller incorporation of firm-specific information in such assets. Hameed et al. (2015) further show that the revision of the earnings forecast of a firm - with high analyst coverage - changes the prices of other firms, whose fundamentals can be predicted by the firm with the high coverage.

Such information spillover effects have been examined both theoretically and empirically. Veldkamp (2006) supports that the observed asset covariance is higher than the one predicted by theoretical models. An explanation is that the lower cost of obtaining high-demand information, leads investors to trade on the same subset of information and signals, increasing asset price comovement. Peng and Xiong (2006) suggest that because of attention capacity constraints, investors need to optimize their attention allocation to reduce their portfolio uncertainty. Under their model, investors tend to obtain more market and industry-wide information, causing return comovement. Similarly, Mondria (2010) shows that investors may use the same signal to update information about two assets, leading to price comovement. They do so because they process a linear combination of asset payoffs.

Based on these theoretical groundings, a number of studies empirically investigate how investors allocate their attention and the implications on stock markets. Leung et al. (2017) construct a measure of co-search of stocks based on Yahoo!Finance, and form clusters of stocks at different points in time. They find that stocks in the same cluster comove, while incorporating the co-search of stocks can improve stock return predictability. Drake et al. (2017) create an attention comovement measure based on Google Trends and measure how much of the variability of a firm's attention is explained by attention to the firm's industry and the market. They find that attention comovement predicts excess stock return comovement, while there is an attention spillover of a firm to peer companies at earnings announcement days. In addition, they use different measure of attention, and show that this relationship does not hold for the co-attention observed through Google SVI (Da et al., 2011).

The concept of co-search and co-attention has been used to predict stock returns in different conditions. Kumar et al. (2017) utilize the co-search measure and study how it affects supply chain connected stock returns. They show that a low (high) co-search between a focal stock and its supply chain partners has high (low) predictability. Jiang et al. (2018) create an asymmetric comovement measure of a stock and the market return and show that a larger downside comovement leads to higher expected returns. Shangguan et al. (2022) create an eigen attention centrality (EAC) measure based on a stock's attention and co-attention with other stocks and provide evidence that their measure is superior in predicting abnormal returns.

Recent studies focus on how market participants allocate their attention between firm-specific and market-wide information. Using large jackpot days, Lin et al. (2019) show that large macro events are able to drive investor attention away from firm-specific stocks. They also associate a higher attention to macroeconomic news with higher comovement between the stock and market returns. Focusing on dual announcements days, i.e., days on which a firm-specific earnings announcement and a macroeconomic announcement co-exist, Liu et al. (2022) investigate whether the relationship between macro and micro-related attention is substitutional or complementary. Their findings suggest that macro news crowd out micro news, leading to distracted investors and to higher earnings surprises. On the contrary, Sheng and Hirshleifer (2022) document a complementary relationship between the two. They argue that the substitutional relationship described by Liu et al. (2022) holds only for retail investors, while the opposite holds for institutional investors. Andrei et al. (2022) provide a theoretical model that supports the complementary relationship.

2.2 Hypotheses development

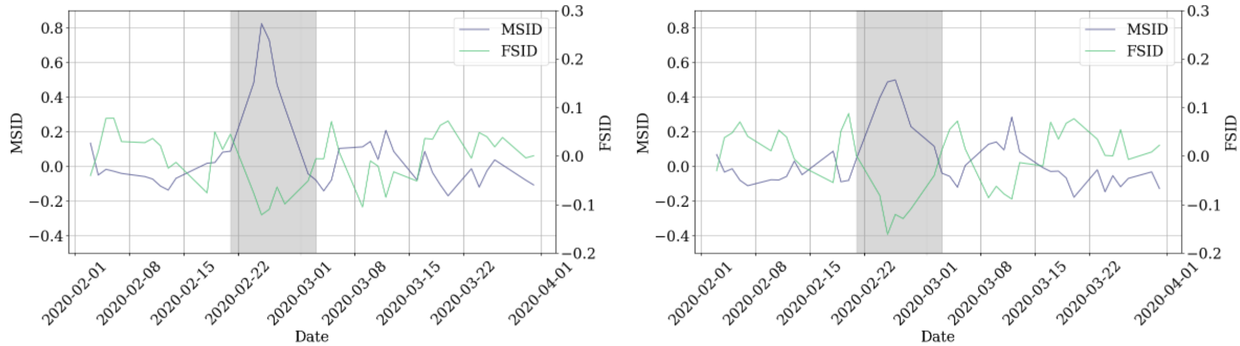
In this section, we present the key hypotheses developed in this study. First, we illustrate the main mechanics of information demand through a recent example for the COVID-19 period, and then we formulate the main hypotheses of this study.

On February 25, 2020, global equity markets suffered their largest two-day decline in four years, with the S&P 500 falling sharply and the Dow registering steep losses that CNBC characterized as the "worst two-day slide in the last four years"[8]. At the same time, the CBOE Volatility Index (VIX) surged 46.6 percent, marking its highest closing level since January 2019[9]. This period was characterized by increased market stress and uncertainty.

As Figure 1 illustrates, this market stress also impacted the way investors allocated their attention during these days. More specifically, the market-specific and firm-specific information demand during February to April 2020. mainly acted as substitutes during that period, with information demand for the market increasing, and firm-specific information demand decreasing accordingly. These extreme market movements underscore the limits of investor attention: as cognitive capacity is finite, investors must allocate their focus among competing information streams (Prat, 1997; Sims, 2003). In periods of acute market stress, aggregate signals—such as steep index declines or VIX spikes—are likely to dominate investors' information sets, drawing attention away from firm-level news. Consequently, we expect market-specific information demand (MSID) and firm-specific information demand (FSID) to function as substitutes: when the first rises due to macro-level shocks, the latter correspondingly declines, and vice versa.

This shift in attention is particularly evident among retail investors. Unlike institutional

[8]https://www.cnbc.com/2020/02/25/stock-market-today-live.html
[9]https://www.nasdaq.com/articles/stock-market-news-for-feb-25-2020-2020-02-25



(a) Website 1 (b) Website 2

This figure shows the MSID and FSID_{agg} as defined in Section 3 during January 2020 to April 2020. The gray area spans between 21st February to 3rd March 2020.

Figure 1: Market-specific and aggregated firm-specific information demand.

investors, who typically possess greater expertise, retail investors are considered less experienced (Boehmer et al., 2021; Barber et al., 2023; Bryzgalova et al., 2023). Consequently, they are more likely to divert their focus away from firm-specific information when faced with dominating market-wide signals. In addition, compared to institutional investors that have access to specialised platforms, retail investors mainly obtain their information through online websites (Da et al., 2011) and search engines. This makes it easier for their attention to be captured by news titles that are designed by specialists to increase the news' visibility.

Our study builds on this literature by leveraging high-frequency data to provide a detailed examination of how retail investors allocate their attention. Specifically, we investigate whether this substitution relationship between MSID and FSID is confined to major distraction events, such as dual announcements (Sheng and Hirshleifer, 2022; Liu et al., 2022), or whether it represents a broader, persistent trend. To the best of our knowledge, we are the first to empirically establish this relationship in a time-series context, offering new insights into the dynamics of retail investor behavior.

H1. Market-wide and firm-specific retail investor information demand are substitutes, consistent with the limited attention hypothesis.

Although we expect the baseline relationship between MSID and FSID to be negative due to investor attention constraints, this substitution effect is likely to be more pronounced during periods of heightened uncertainty. For example, on February 25, 2020, the onset of COVID-19-related market stress triggered a substantial increase in the CBOE Volatility Index (VIX). In response, this created an even larger motive for investors to focus on this market-wide effect, reducing even further their attention allocation to specific firms.

A broad literature in economics and finance links uncertainty with patterns of information acquisition. Foundational work by Kahneman (1973) and Shannon (1948), as well as formal models of rational inattention and coordination games (e.g., Sims, 2003; Veldkamp, 2011; Andrei and Hasler, 2014; Orlik and Veldkamp, 2015), suggest that agents selectively acquire information that most efficiently reduces uncertainty around future outcomes. When uncertainty is elevated, investors tend to prioritize broad market signals, such as volatility indices or macroeconomic news, over idiosyncratic firm-level updates. These signals are perceived to carry more salient, system-wide implications during such periods.

Following the theoretical argument, we expect MSID and FSID to be linked to market uncertainty. As they face uncertainty, information acquisition becomes their primary mechanism of resolving it, leading to signals perceived as more informative and actionable (Hellwig and Veldkamp, 2009; Peng and Xiong, 2006). Therefore, in periods of higher market uncertainty, retail investors are expected to focus on market-wide signals and in response reduce their attention allocation to firm-specific information due to attention capacity constraints.

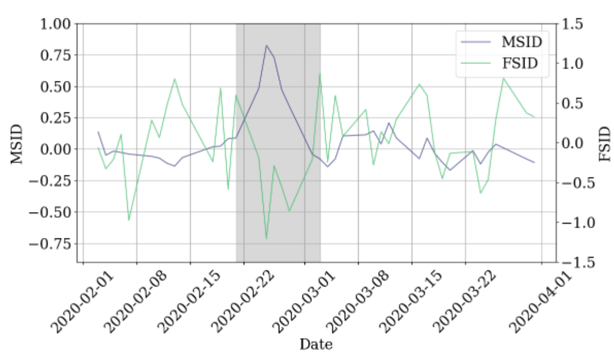
H2. Periods of increased market uncertainty increase the demand for information from retail investors in the market while decreasing the demand for firm-specific information.

Existing theoretical studies suggest that due to limited attention and strategic motives (Hellwig and Veldkamp, 2009) investors may use a market-wide signal to adjust their beliefs in individual assets. As investors process a linear combination of asset payoffs and update their beliefs on a unified signal, this may lead to the synchronicity of the firm price with the market price (Mondria, 2010). On the contrary, when investors increase their firm-specific focus, this increases the idiosyncratic information incorporated in asset prices. In this case, we'd expect that higher FSID will decrease the information demand synchronicity and subsequently decrease the stock price synchronicity.

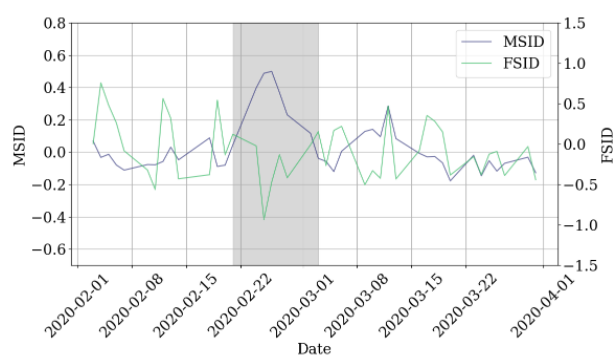
As attention distraction has been shown to be more prominent for retail investors (Sheng and Hirshleifer, 2022; Liu et al., 2022), we'd expect that the synchronicity in retail investor attention is more likely to drive price synchronicity. However, literature has produced mixed findings on this matter. Lin et al. (2019) use external events as sources of distraction and show that during such days there is indeed a higher synchronicity of the stock with the market returns. The findings are more pronounced for high retail ownership stocks. Drake et al. (2017) utilize two measures of institutional investor attention and one measure of retail investor attention, and they show that the retail investor firm-specific attention has the smallest comovement with the market and industry-wide attention, while across these metrics, it is the only one that has no contemporaneous nor predictability significance on the returns comovement.

We argue that the source of the contradictory findings lies in the measures used in the respective studies and the nature of the synchronicity measure employed. The use of specific distraction days by Lin et al. (2019) may not be indicative of the dynamic relationship between attention and stock return synchronicity. Drake et al. (2017) use an aggregate firm-specific measure as a market attention measure instead of a measure that is directly related to the attention paid to the market. If our *Hypothesis 1* holds, such a measure will be negatively connected to MSID and hence produce counterintuitive findings. Additionally, the measure used to capture synchronicity (typically the R^2 from the regression of the variables in question) does not provide any insights into the relationship between the measures the synchronicity is calculated upon and hence it can not distinguish whether the observed comovement is caused by attention distraction or enhancement.

To address this ambiguity, we explicitly examine the joint dynamics of MSID and FSID. In particular, we isolate cases in which FSID and MSID exhibit a negative relationship, indicative of attention substitution. Under conditions of elevated market uncertainty, where market-wide attention dominates, we expect both MSID and return synchronicity to increase, reflecting greater co-movement driven by common shocks. In contrast, when attention shifts toward firm-specific information—allowing idiosyncratic signals to be more fully incorporated into prices—we expect both FSID and return synchronicity to decline. By disentangling these cases, we provide a clearer interpretation of the informational underpinnings of return synchronicity.



(a) Website 1



(b) Website 2

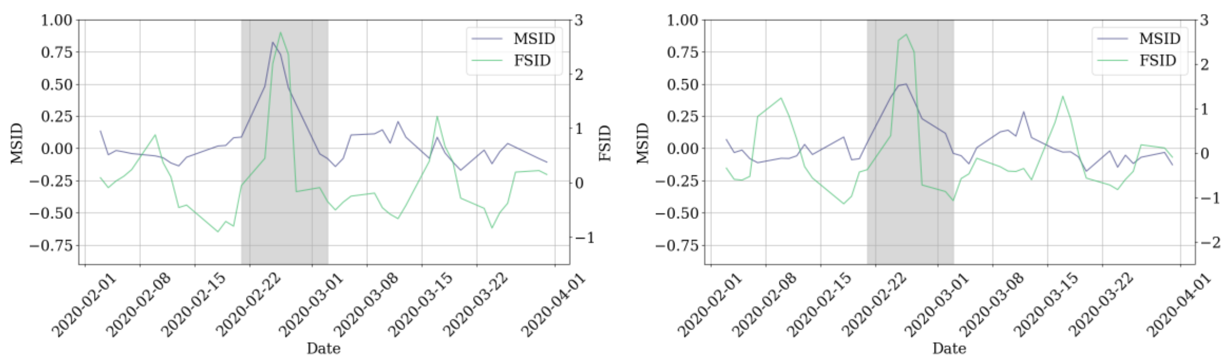
This figure shows the MSID and FSID for S&P Global Inc. (ticker: SPGI) as defined in Section 3 during January 2020 to April 2020. The gray area spans between 21st February to 3rd March 2020.

Figure 2: Information demand for S&P Global Inc. (SPGI).

H3. When market-wide and firm-specific information demands are negatively correlated, increased (decreased) synchronicity in information demand leads to increased (decreased) synchronicity in stock returns.

Prior literature has documented both a crowding-out and an attention-enhancement in the face of dual announcement days. Liu et al. (2022) find that the difference in the mechanisms come from different types of investors, with retail (institutional) investors decreasing (increasing) their firm-specific focus on days where both a firm announcement and a macroeconomic announcement take place. In this study, we show that for retail investors, these mechanisms can co-exist.

Figure 3 illustrates the distraction mechanism, as shown for S&P Global Inc. at the example period. Consistent with our prior hypotheses, FSID decreases markedly, suggesting that the release of market-wide news diverted attention away from the firm. However, not all firms experience attention decay under these conditions. Instead, we find that market-wide uncertainty can amplify attention to specific firms. For example, during the onset of the COVID-19 crisis, information demand for Moderna Inc., a key vaccine developer, spiked sharply (Figure 2). Similar surges were observed for firms like Netflix, Disney, and major airline carriers, some of which were closely tied to pandemic-related themes.



(a) Website 1 (b) Website 2

This figure shows the MSID and FSID for Moderna Inc. (ticker: MRNA) as defined in Section 3 during January 2020 to April 2020. The gray area spans between 21st February to 3rd March 2020.

Figure 3: Information demand for Moderna Inc. (MRNA).

Following this we expect to find some novel dynamics between the information demand and stock price synchronicity. First, we expect to find that a spillover mechanism exists, under which an increase in MSID will lead to an increase in FSID, and hence increase the firm-specific information incorporated in prices, decreasing the stock price synchronicity. Firms that exhibit a lower information spillover from the market will have a lower information demand, in which case the market-specific signals will dominate, creating lower returns synchronicity. Finally, in situations where retail investor attention is diffusely allocated or entirely distracted, resulting in muted demand for both FSID and MSID, we expect higher levels of pricing noise and thus reduced synchronicity, consistent with less informative prices.

H4. When market-wide and firm-specific information demands are positively correlated, increased (decreased) synchronicity in information demand leads to decreased (increased) synchronicity in stock returns.

Prior literature shows that retail investors primarily drive the crowding out of firm-specific information during periods of heightened distraction. It suggests that, as retail investors are generally less sophisticated, they are more prone to cognitive biases and shifts in attention (Boehmer et al., 2021; Barber et al., 2023). Importantly, Lin et al. (2019) document that during exogenous distraction events, stocks with higher retail ownership exhibit greater price synchronicity with the market, consistent with the divergence of attention from firm-specific information. Sheng and Hirshleifer (2022); Liu et al. (2022) show that retail investors mainly experience attention distraction on the presence of both macro and micro news.

Following these studies, we would initially expect that firms with higher retail ownership would primarily drive the negative relationship between MSID and FSID. However, this is counterintuitive if our *Hypotheses* hold. If retail investors exhibit both crowding-out and spillover effects, the choice of which signals to observe would be based on the firms' characteristics. In the example presented, some firms will experience attention distraction, and some attention enhancement. It is reasonable for an investor for this case to choose to obtain information about a firm that she already holds in her portfolio or that has greater potential to produce positive returns. At the same time, the attention paid to firms owned less by retail investors will experience a large attention crowding-out for multiple reasons.

First, institutional investors quickly incorporate both macro and micro signals into prices. Retail investors, who are slower to process complex information, may find themselves crowded out of firm-specific attention under such conditions. This dynamic is especially pronounced in firms with high institutional ownership, where professional investors react swiftly to macro developments, amplifying the dominance of market-specific signals. At the same time, when there is higher uncertainty, retail investors will obtain more information for stocks they may already own, creating a higher distraction for higher institutional ownership firms.

H5. The crowding-out (spillover) effect is more prominent for firms with higher (lower) institutional ownership.

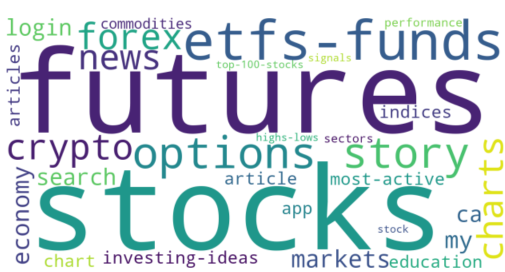
3 Data and sample construction

3.1 Information demand

3.1.1 Data

We obtain online traffic data from an audience intelligence platform that monitors user activity on more than 200 websites. This platform records every click made by users who have consented to website cookie policies, covering activity in the United States and Canada during the period from November 2017 to December 2023. The data set includes a diverse range of financial and media websites, such as stock screeners, company filing repositories, financial news portals, general media publishers, and online trading platforms.

Within this dataset, we manually identify five websites that rank among the top 50 "Finance-Investing" websites in the United States and ten websites that are in the top 100, according to Similarweb rankings[10]. For our analysis, we focus on the click-level activity from two websites, Website 1 and Website 2 consistently ranked among the top 30 in this category, ensuring long-term data coverage. Both websites are present in the sample from November 2017 to February 2023. We identified a four-month data gap for Website 2 between May and August 2022 and, consequently, excluded this period from our analysis.



(a) Wordcloud for Website 1.

(b) Wordcloud for Website 2.

This figure shows the different categories identified in each website through the URLs. The size of the words are relative to the number of clicks for each category in our sample.

Figure 4: Websites' high-level information categories.

Once a user accesses a website within the respective tracking network, the system assigns a masked user ID that remains persistent between different websites in the data set. This identifier is linked to the browser rather than the user's geographic location and remains active unless the user clears their cookies. The data set records the exact timestamp of

[10] The ratings were obtained on May 2024.

each click, measured in Coordinated Universal Time (UTC), the website name as the data provider identifies this, the specific URL visited by the user, and the anonymized user ID.

We employ two necessary data-cleaning mechanisms. First, we remove duplicated clicks assigned to the same user and URL, but they either have the same timestamp or a difference of one second. These cases likely reflect a connection failure rather than distinct user interactions. Although there are some duplicates with two-second differences, we cannot be certain if these are created because of a page refresh or a duplicated click. Second, based on all of the websites, we remove any scrappers by removing from the data users linked to more than 2,400 clicks in a day, after we have removed the duplicated values. This threshold is based on the assumption that an individual can view a maximum of 100 pages per hour[11].

Next, we identify each website through the website classification provided to us by the data provider. We normalize all the URLs bringing them to the same format *https://www.{*.}domain.com*. To classify the URLs to specific tickers it is necessary to know the structure of the URLs for each website. To accomplish this, we collect for each website the unique URLs as these appear in our sample for the 15$^{\text{th}}$ of every third month (March, June, September, December) for every year. We go through these separately for each website and identify the regular expressions that identify the ticker in each website-section pair. Figure 4 shows the high-level categories of each website. These come from almost 832 million clicks from Website 1 and nearly 1.3 billion clicks from Website 2, respectively. Table 1 presents the main descriptive statistics of our sample.

	Website 1					Website 2				
	Mean	SD	25$^{\text{th}}$	50$^{\text{th}}$	75$^{\text{th}}$	Mean	SD	25$^{\text{th}}$	50$^{\text{th}}$	75$^{\text{th}}$
Users	5,533	4,327	2,283	4,035	7,496	9,378	7,412	3,876	6,953	12,126
URLs	4,564	2,696	2,434	4,031	6,375	7,740	5,575	3,646	6,625	10,232
N. clicks	17,924	14,715	7,230	12,809	24,770	29,294	25,193	11,052	21,317	39,372

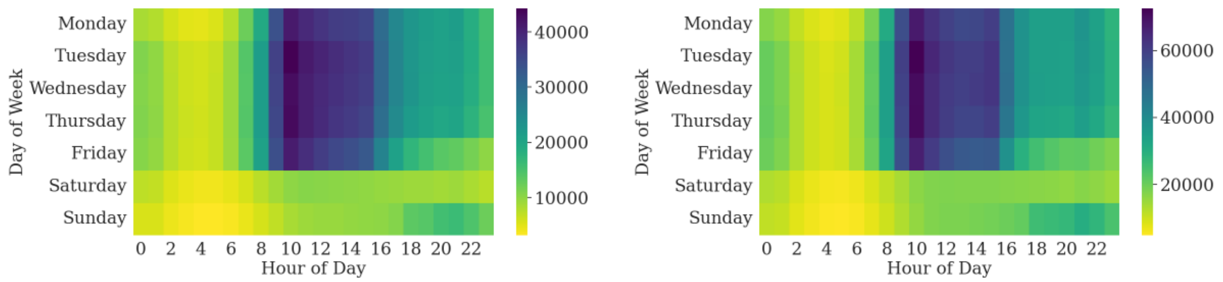
This table provides the hourly descriptive statistics for the two websites utilized in our analysis. (a) *Users* refers to the unique users identified per hour; (b) *URLs* refers to the unique URLs visited per hour; (c) *N. clicks* refers to the number of clicks per hour.

Table 1: Summary hourly statistics of click activity.

Figure 5 illustrates user activity during the week and hours of the day. We observe a clear concentration of engagement during standard trading hours (9:00 AM to 4:00 PM), consistent with prior findings. In particular, user activity drops off more sharply after Friday trading hours than other weekdays. Figure 6 presents the activity of the users by day of the

[11]Note that some clicks might be created only through a change in the timeframe of a stock screening web page. In such cases, the alternation between pages can happen within even the same second.

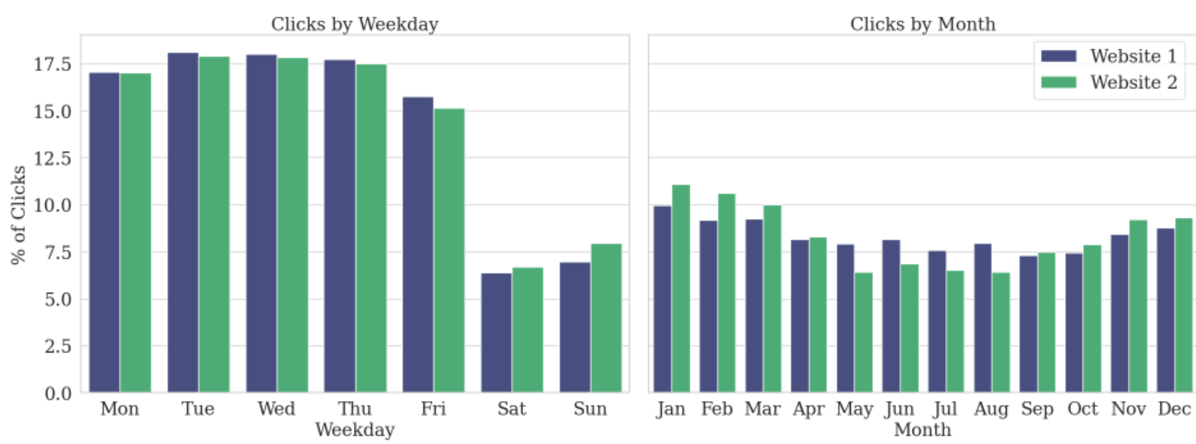
week and month of the year. In line with previous literature, we find reduced participation on weekends and increased activity on Tuesdays and Wednesdays (Liu et al., 2022). However, unlike Liu et al. (2022), who report that retail investor activity on Fridays closely resembles weekend levels, our data show that Friday engagement remains substantially higher. In addition, we find a pronounced decline in user activity during the summer months (May to September). These patterns are consistent across both websites analyzed in this study.



(a) Heatmap for Website 1. (b) Heatmap for Website 2.

This figure shows the heatmap of the clicks for each website based on the day-of-the-week and the hour-of-the-day. Darker (lighter) areas reflect more (less) clicks.

Figure 5: User activity per day of the week and hour of the day.



This figure shows the percentage of clicks identified for each website based on the week-of-the-day and month-of-the-year. The purple (green) bars reflect the clicks on Website 1 (Website 2).

Figure 6: User activity per day of the week and month of the year.

3.1.2 Measures

We capture the demand for firm- and market-specific information through our sample's daily number of clicks. For each day (t), we count the number of clicks between 4 PM of the previous day ($t-1$) until 4 PM of the current day. We create all the measures based on the scaled clicks, defined as the daily number of clicks for an entity divided by the daily total number of clicks on the respective website after the cleaning process. We define:

$$\mathrm{N}_{clicks,i,t} = \sum_{16:00_{t-1}}^{16:00_t} clicks_{i,t}, \quad \mathrm{N}^{total}_{clicks,t} = \sum_{16:00_{t-1}}^{16:00_t} clicks_t, \quad \mathrm{N}^{sc}_{clicks,i,t} = \frac{\mathrm{N}_{clicks,i,t}}{\mathrm{N}^{total}_{clicks,t}},$$

where $clicks_{i,t}$ is the number of clicks for an entity i of day t. Entity i may be either a ticker or a collection of tickers. The $\mathrm{N}^{total}_{clicks,t}$ captures the summation of the clicks from our whole sample after the data cleaning process described in Section 3. It includes the clicks connected to tickers and those that remained unidentified. In the cases where t is a Monday, we use the average of the number of clicks for an entity (or for the total number of clicks) between the closing of Friday at 4 PM and the closing of Monday at 4 PM.

We create a measure that captures the firm-specific information demand (FSID) for each firm in our sample (i is the respective firm ticker). Also, we create a measure that captures the market information demand (MSID) by aggregating the clicks linked to S&P 500, Dow Jones, Nasdaq, and Russel (i represents the collection of tickers linked to these indices). For each of these measures, we create short-term metrics to capture short-term variations in information demand, and long-term metrics to reflect long-run information demand changes. These are created based on a similar way to the Google ASVI (Da et al., 2011):

$$\mathrm{FSID}^{7}_{i,t} = \ln\left(\frac{\mathrm{ID}_{i,t}}{\mathrm{Med}(\mathrm{ID}_{i,t-1},\ldots,\mathrm{ID}_{i,t-1-T})}\right), \quad \text{where} \quad \mathrm{ID}_{i,t} = \frac{\mathrm{N}^{sc}_{\mathrm{clicks},i,t}}{\max(\mathrm{N}^{sc}_{\mathrm{clicks},i})} \times 100, \tag{1}$$

$$\mathrm{MSID}^{7}_{t} = \ln\left(\frac{\mathrm{ID}_{i,t}}{\mathrm{Med}(\mathrm{ID}_{i,t-1},\ldots,\mathrm{ID}_{i,t-1-T})}\right), \quad \text{where} \quad \mathrm{ID}_{i,t} = \frac{\mathrm{N}^{sc}_{\mathrm{clicks},i,t}}{\max(\mathrm{N}^{sc}_{\mathrm{clicks},i})} \times 100, \tag{2}$$

where FSID in constructed for each firm (i) in our sample, and MSID is created based on the number of clicks in the indices mentioned.

Note that Da et al. (2011) constructs ASVI based on monthly searches, utilizing a 2-month horizon, whereas our data allow for the construction of metrics on a higher frequency.

The main measures in this study are FSID^7 and MSID^7, which are constructed based on the past 5 business days. In addition, we report the results for FSID^T and MSID^T where $T \in \{14, 30, 60\}$, which are calculated based on the past 10, 20, and 45 business days medians. We skip the most recent day in the median calculation for $T \in \{7, 14\}$ and the most recent 5 business days in the median calculation for $T \in \{30, 60\}$.

To account for day-of-the-week effects in our sample, we detrend each time series (for each entity i) through regressions on day-of-the-week dummies[12]. This reduces any constant movements of the information demand metrics, which are caused by fixed effects such as the Monday effect, rather than changes in information demand attitudes.

Through the metrics calculated for each firm in our sample, we create a measure that reflects the aggregate firm-specific information demand (FSID_{agg}). This is calculated as the daily average of the FSID metrics presented for each day in our sample. This measure is constructed through a similar way to the one utilized in Drake et al. (2017). The descriptive statistics of the MSID and FSID_{agg} metrics are presented in Table 2.

3.2 Macroeconomic variables and firm characteristics

As part of our analysis we use a wide range of existing uncertainty measures at daily and monthly frequencies. More specifically, we use the CBOE equity volatility index (VIX), which has been consistently considered as a proxy of market uncertainty by several previous studies (e.g., Cascaldi-Garcia and Galvao, 2021; Bekaert and Hoerova, 2016; Novy and Taylor, 2020). The VIX is based on the implied volatility of 1-month maturity options on the S&P 500, and therefore is considered to capture financial uncertainty. Due to stationarity issues, we use the first difference of the daily VIX values in all the regression analyses. In addition, we use the monthly Economic Policy Uncertainty index (EPU) (Baker et al., 2016), as well as the financial (LD-Financial), real (LD-Real), and macroeconomic (LD-Macro) uncertainty indices derived in Ludvigson et al. (2015, 2021) for the 1-month horizon. These are downloaded from the authors' website.

Individual stock returns and firm characteristics are calculated using the Center for Research in Security Prices (CRSP) and Compustat databases through Wharton Research Data Services (WRDS). Institutional ownership data are retrieved through Thomson Reuters 13F merged with CRSP stock split adjustments. Analysts' data are retrieved from the Thomson Reuters I/B/E/S database. We construct a wide range of quarterly control variables. In particular we measure the logarithm of market capitalisation (ln(MktCap)), return on assets (ROA), book to market ratio (BkMkt), sales growth (Sales), standard deviation of ROA

[12]We use Wednesday as the default, but the results remain for different modifications.

in the past year (StdROA), price (Price), Tobin's Q, institutional ownership (IO) and the number of analysts following a firm (# Analysts) for every quarter-firm pair. The descriptive statistics of the firm characteristics are presented in Table 2.

3.3 Sample construction

We merge the identified tickers with the CRSP database to construct our sample. Specifically, we focus on stocks listed on major exchanges (NYSE, AMEX, and NASDAQ) with an exchange code (exchcd) of 1, 2, 3, or 4 and a share code (shrcd) of 10 or 11. To ensure sufficient liquidity, we retain only stocks with a closing price above $5 at the previous year, resulting in an initial sample of 5086 and 4973 firms for Websites 1 and 2, respectively.

To refine our dataset further, we impose additional filters. We include only firms with at least one year of presence in the dataset. Moreover, to mitigate the influence of extreme outliers, we include only firms with more than 252 trading days of non-zero clicks. After applying these criteria, our final sample contains 3,510 and 3,845 firms for Websites 1 and 2, respectively, which form the basis of our empirical analysis.

	Website 1			Website 2		
	Mean	Median	StDev	Mean	Median	StDev
Panel A: Firm characteristics						
ln(MktCap)	7.736	7.682	1.814	7.588	7.545	1.863
ROA	0.001	0.006	0.045	0.001	0.006	0.044
BkMkt	0.498	0.386	0.485	0.516	0.404	0.491
Sales	1.076	1.024	0.442	1.075	1.022	0.452
StdROA	0.018	0.009	0.029	0.018	0.009	0.030
Price	61.747	35.110	80.757	59.749	33.750	78.413
IO	0.726	0.812	0.266	0.706	0.798	0.278
# Analysts	10.240	8.000	8.683	9.784	8.000	8.748
Tobin's Q	2.392	1.588	2.145	2.370	1.548	2.165
Panel B: Information demand						
MSID^{7}	0.000	-0.011	0.122	0.000	-0.019	0.126
MSID^{14}	0.000	-0.022	0.141	0.000	-0.020	0.152
MSID^{30}	0.000	-0.034	0.189	0.000	-0.025	0.214
MSID^{60}	0.000	-0.042	0.214	0.000	-0.030	0.238
FSID^{7}_{agg}	0.000	-0.002	0.053	0.000	0.003	0.050
FSID^{14}_{agg}	0.000	-0.001	0.059	0.000	0.004	0.055
FSID^{30}_{agg}	0.000	0.001	0.080	0.000	0.001	0.071
FSID^{60}_{agg}	0.000	-0.005	0.086	0.000	-0.001	0.075

This table provides the descriptive statistics of the sample. Panel A includes the quarterly firm characteristics' mean, median, and standard deviation values. Panel B contains the same statistics for the MSID measures and FSID_{agg} reflecting the firm aggregation metric.

Table 2: Descriptive statistics of the firm characteristics and information demand metrics.

4 Empirical analysis

4.1 Market and firm-specific information demand

This section investigates the relationship between market-specific and firm-specific information demand. Table 2 presents descriptive statistics for MSID and FSID_{agg}. Since these variables are computed as residuals from regressions on day-of-the-week dummy variables, their average values are close to zero. The median values of MSID are consistently negative, suggesting right-skewed distributions, whereas FSID_{agg} measures exhibit less pronounced skewness, with median values varying across metrics and websites. The standard deviations of MSID metrics are larger than those of FSID_{agg}, as expected, given that market-wide information demand captures a broader distribution of clicks relative to firm-level measures. These patterns are consistent across all time horizons (T) considered.

Table 3 reports the correlation coefficients between MSID and FSID_{agg}, along with their corresponding significance levels. The correlations range from -33% to -50% for Website 1 and from -36% to -56% for Website 2. Correlations are more negative at longer aggregation horizons (T), reflecting greater persistence of the metrics over time. Although persistence increases with T, unit root tests indicate that all variables remain stationary, supporting their suitability for regression analysis.

We further examine the contemporaneous relationship between MSID and FSID_{agg} by estimating the following system of regressions for each aggregation horizon $T \in \{7, 14, 30, 60\}$:

$$\text{MSID}_t^T = \alpha + \sum_{k=1}^{4} \beta_k \, \text{MSID}_{t-k}^T + \sum_{k=0}^{4} \gamma_k \, \text{FSID}_{\text{agg},t-k}^T + \epsilon_t, \tag{3a}$$

$$\text{FSID}_{\text{agg},t}^T = \alpha + \sum_{k=1}^{4} \beta_k \, \text{FSID}_{\text{agg},t-k}^T + \sum_{k=0}^{4} \gamma_k \, \text{MSID}_{t-k}^T + \epsilon_t. \tag{3b}$$

In this specification, MSID_t^T ($\text{FSID}_{\text{agg},t}^T$) denotes the market-specific (firm-specific average) information demand at time t, based on a moving window of length T days. Each regression includes four lags of both the dependent and independent variables to account for short-term persistence and potential dynamic feedback effects. The results are reported in Panel A of Table 4. For brevity, the coefficients and significance levels of the lagged dependent variables are omitted from the table but are available upon request.

	1. ΔVIX	1. LD-Financial	3. LD-Macro	4. LD-Real	5. EPU	6. MSID^7	7. MSID^{14}	8. MSID^{30}	9. MSID^{60}	10. FSID$^7_{agg}$	11. FSID$^{14}_{agg}$	12. FSID$^{30}_{agg}$
Panel A: Website 1												
3.		0.388***										
4.		0.413***	0.964***									
5.		0.324**	0.526***	0.487***								
6.	0.185***	-0.067	0.211	0.171	-0.061							
7.	0.134***	-0.046	0.244*	0.204	-0.025	0.937***						
8.	0.114***	-0.028	0.318**	0.262**	0.213*	0.669***	0.826***					
9.	0.088***	0.001	0.371***	0.292**	0.352***	0.497***	0.640***	0.914***				
10.	-0.150***	-0.182	0.140	0.197	0.046	-0.333***	-0.330***	-0.227*	-0.181			
11.	-0.135***	-0.206	0.073	0.136	-0.019	-0.374***	-0.384***	-0.319**	-0.290**	0.973***		
12.	-0.107***	-0.210	-0.053	0.025	-0.180	-0.279**	-0.346***	-0.458***	-0.465***	0.757***	0.860***	
13.	-0.079***	-0.251**	-0.123	-0.032	-0.339***	-0.203	-0.258**	-0.413***	-0.497***	0.601***	0.712***	0.921***
Panel B: Website 2												
3.		0.388***										
4.		0.413***	0.964***									
5.		0.324**	0.526***	0.487***								
6.	0.199***	-0.032	0.128	0.106	-0.138							
7.	0.163***	-0.014	0.142	0.112	-0.097	0.956***						
8.	0.115***	-0.005	0.173	0.115	0.088	0.699***	0.817***					
9.	0.095***	0.034	0.220	0.143	0.228*	0.560***	0.661***	0.926***				
10.	-0.226***	0.037	0.122	0.165	0.149	-0.361***	-0.400***	-0.378***	-0.317**			
11.	-0.189***	-0.010	-0.016	0.032	0.056	-0.448***	-0.507***	-0.516***	-0.465***	0.939***		
12.	-0.139***	-0.033	-0.217	-0.152	-0.130	-0.429***	-0.483***	-0.575***	-0.557***	0.621***	0.816***	
13.	-0.116***	-0.067	-0.322**	-0.245*	-0.343**	-0.358***	-0.393***	-0.482***	-0.557***	0.364***	0.584***	0.889***

This table reports the Pearson correlation coefficients among the information demand variables of Website 1 (Panel A) and Website 2 (Panel B) used in the analysis and various uncertainty metrics. Correlations are based on daily frequency for ΔVIX, and monthly frequency for the rest of the variables. The Monthly MSID and FSID metrics are constructed through averaging the variables within a given month. Statistical significance is indicated by *, **, and *** corresponding to the 10%, 5%, and 1% significance levels, respectively.

Table 3: Correlation matrices.

In line with the correlation coefficients and *Hypothesis 1*, we document a negative relationship between MSID and FSID_{agg}, consistent with the notion that these forms of information demand act as substitutes. The limited attention theory (Prat, 1997; Sims, 2003) posits that investors, constrained by cognitive capacity, must selectively process information and cannot absorb all available signals simultaneously. This constraint naturally generates a negative association between MSID and FSID_{agg}, particularly given that FSID_{agg} reflects the average level of firm-specific information demand, rather than firm-specific idiosyncratic information demand dynamics.

The estimated coefficients on FSID_{agg} range from -0.35 to -0.39 for Website 1 and from -1.05 to -1.10 for Website 2, and are statistically significant across specifications. The negative sign and sizable magnitude of these coefficients suggest that increases in market-wide attention are associated with economically meaningful declines in firm-specific information demand. Furthermore, the adjusted R^2 increases with the aggregation horizon T, reflecting greater persistence of the underlying variables at longer horizons. Specifically, as T increases from 7 to 60 days, the adjusted R^2 rises from 0.39 to 0.81 for Website 1 and from 0.46 to 0.86 for Website 2. Similar patterns emerge when MSID is used to explain FSID_{agg}, although the corresponding coefficients are smaller in magnitude.

These findings contribute to the literature on investor attention by highlighting important distinctions between measures of firm-specific and market-wide information demand. While Drake et al. (2017) constructs a market attention proxy using a methodology similar to FSID_{agg}, our results suggest that average firm and actual market-level attention move in opposite directions, reflecting fundamentally different investor information acquisition preferences. In particular, periods of heightened market attention are associated with reduced attention to individual firms, suggesting that aggregate shocks induce a reallocation of attention away from idiosyncratic information toward broader market signals.

4.2 Information demand and uncertainty

This section examines the relationship between information demand and various measures of uncertainty. Several strands of the literature motivate this analysis. First, recent work shows that investor click activity itself can serve as a direct proxy for uncertainty (Benamar et al., 2021). In addition, theoretical models suggest that the attention distraction effect on stock price synchronicity is amplified by heightened market uncertainty (Hellwig and Veldkamp, 2009). In periods of elevated uncertainty, limited investor attention may shift toward broad market signals, prompting trading behavior based on common information sets and increasing the synchronicity between individual asset prices and the market.

	Website 1				Website 2			
Panel A: Firm and market specific information demand								
	$MSID^7$	$MSID^{14}$	$MSID^{30}$	$MSID^{60}$	$MSID^7$	$MSID^{14}$	$MSID^{30}$	$MSID^{60}$
$MSID^T_{t-1}$	0.615***	0.722***	0.788***	0.788***	0.535***	0.662***	0.726***	0.724***
	(0.042)	(0.047)	(0.037)	(0.037)	(0.045)	(0.047)	(0.045)	(0.045)
$FSID^T$	-0.354***	-0.371***	-0.386***	-0.388***	-1.052***	-1.113***	-1.107***	-1.102***
	(0.075)	(0.077)	(0.077)	(0.078)	(0.106)	(0.119)	(0.117)	(0.121)
$FSID^T_{t-1}$	-0.026	0.013	0.032	0.037	0.358***	0.552***	0.653***	0.654***
	(0.072)	(0.073)	(0.076)	(0.077)	(0.098)	(0.108)	(0.114)	(0.113)
Intercept	0.000	0.000	-0.001	-0.001	0.000	0.000	0.000	0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Adjusted R^2	0.390	0.553	0.757	0.813	0.457	0.634	0.818	0.857
	$FSID^7$	$FSID^{14}$	$FSID^{30}$	$FSID^{60}$	$FSID^7$	$FSID^{14}$	$FSID^{30}$	$FSID^{60}$
$FSID^T_{t-1}$	0.410***	0.474***	0.548***	0.540***	0.509***	0.591***	0.681***	0.674***
	(0.032)	(0.031)	(0.031)	(0.032)	(0.043)	(0.044)	(0.042)	(0.045)
$MSID^T$	-0.083***	-0.087***	-0.092***	-0.092***	-0.175***	-0.182***	-0.178***	-0.181***
	(0.015)	(0.015)	(0.016)	(0.016)	(0.018)	(0.019)	(0.020)	(0.020)
$MSID^T_{t-1}$	0.018	0.029	0.030	0.036*	0.089***	0.103***	0.113***	0.115***
	(0.017)	(0.018)	(0.019)	(0.019)	(0.017)	(0.019)	(0.019)	(0.020)
Intercept	0.000	0.000	-0.001	0.000	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Asjusted R^2	0.232	0.397	0.671	0.727	0.432	0.547	0.730	0.764
Panel B: Information demand and uncertainty								
	$MSID^7$	$MSID^{14}$	$MSID^{30}$	$MSID^{60}$	$MSID^7$	$MSID^{14}$	$MSID^{30}$	$MSID^{60}$
$MSID^T_{t-1}$	0.540***	0.654***	0.741***	0.710***	0.451***	0.583***	0.664***	0.640***
	(0.037)	(0.040)	(0.042)	(0.034)	(0.042)	(0.044)	(0.049)	(0.043)
ΔVIX	0.014***	0.014***	0.014***	0.014***	0.014***	0.015***	0.014***	0.015***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
ΔVIX_{t-1}	0.017***	0.017***	0.017***	0.018***	0.019***	0.019***	0.018***	0.019***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Intercept	0.000	-0.001	-0.001	-0.001	0.000	0.000	0.000	0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Adjusted R^2	0.490	0.630	0.797	0.847	0.465	0.634	0.815	0.858
	$FSID^7$	$FSID^{14}$	$FSID^{30}$	$FSID^{60}$	$FSID^7$	$FSID^{14}$	$FSID^{30}$	$FSID^{60}$
$FSID^T_{t-1}$	0.383***	0.446***	0.514***	0.507***	0.435***	0.522***	0.601***	0.589***
	(0.031)	(0.031)	(0.030)	(0.031)	(0.034)	(0.033)	(0.033)	(0.033)
ΔVIX	-0.005***	-0.005***	-0.005***	-0.005***	-0.007***	-0.007***	-0.007***	-0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ΔVIX_{t-1}	-0.006***	-0.006***	-0.006***	-0.006***	-0.007***	-0.007***	-0.007***	-0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Intercept	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Adjusted R^2	0.286	0.437	0.697	0.748	0.450	0.552	0.737	0.770

This table presents results from time-series regressions analyzing the contemporaneous relationship between MSID and $FSID_{agg}$ (Panel A); MSID and ΔVIX and $FSID_{agg}$ and ΔVIX (Panel B). Each regression includes four lags of each variable and the contemporaneous term of the independent variable. All standard errors are computed using the Newey-West procedure to correct for heteroskedasticity and autocorrelation up to 10 lags. Significance levels are indicated by *, **, and *** for 10%, 5%, and 1% levels, respectively.

Table 4: Contemporaneous regressions of MSID, $FSID_{agg}$ and ΔVIX.

Table 3 reports the correlations between information demand metrics and the uncertainty measures employed in this study. As a proxy for financial uncertainty, we first use the daily VIX index, widely adopted in the literature. Correlations between MSID, FSID$_{agg}$, and ΔVIX are computed at daily frequency. For monthly uncertainty proxies, MSID and FSID$_{agg}$ are aggregated to the monthly level by averaging daily observations within each month to ensure temporal alignment.

Consistent with the limited attention mechanism, we find that MSID is significantly positively correlated with ΔVIX, whereas FSID$_{agg}$ is significantly negatively correlated with ΔVIX. The magnitude of the positive correlation between MSID and ΔVIX ranges from 11.4% to 18.5% for Website 1 and from 9.5% to 19.9% for Website 2. In contrast, the correlation between FSID$_{agg}$ and ΔVIX ranges from -15.0% to -7.9% for Website 1 and from -22.6% to -11.6% for Website 2. These results are statistically significant across all aggregation horizons (T) considered and are robust across both data sources. Overall, the findings support the interpretation that elevated financial market uncertainty reallocates investor attention from firm-specific to market-wide information.

The monthly uncertainty indices are all positively and statistically significantly correlated with one another; however, their relationships with MSID and FSID$_{agg}$ are more nuanced. The EPU index exhibits similar dynamics to ΔVIX primarily for metrics computed over longer aggregation horizons (T). For Website 1 (Website 2), the correlations between EPU and MSID are 21.3% (8.8%) and 35.2% (22.8%) for $T \in \{30, 60\}$, respectively, while the correlations between EPU and FSID$_{agg}$ are -18.0% (-13.0%) and -33.9% (-34.3%) for the same horizons. In contrast, for shorter aggregation horizons ($T \in \{7, 14\}$), the correlations between EPU and the information demand metrics are statistically insignificant, and in most cases, of the opposite sign. This pattern suggests that uncertainty captured by EPU affects investor information demand primarily over longer horizons, consistent with the notion that policy-related uncertainty evolves more slowly and impacts investor behavior over extended periods rather than day-to-day market dynamics.

The LD uncertainty indices exhibit broadly similar patterns. The financial uncertainty index (LD-Financial) is negatively correlated with FSID$_{agg}$, although the correlation is statistically significant only for Website 1 at $T = 60$. Correlations between LD-Financial and MSID are small, negative, and statistically insignificant across all horizons. In contrast, both the macroeconomic (LD-Macro) and real (LD-Real) uncertainty indices are positively correlated with MSID, with correlation magnitudes increasing at longer horizons (T), and significance achieved only for Website 1. Their correlations with FSID$_{agg}$ are generally insignificant except at $T = 60$, where they are negative and statistically significant, consistent with earlier results linking higher uncertainty to a shift away from firm-specific information.

Notably, at the shortest horizon ($T = 7$), both LD-Macro and LD-Real indices are positively correlated with both MSID and FSID_{agg}. This suggests more complex short-run dynamics, potentially reflecting heterogeneous investor responses to different types of uncertainty, a possibility that we investigate further in the subsequent analysis.

We establish the contemporaneous relationship between daily information demand and VIX by estimating the following system of regressions for each aggregation horizon $T \in \{7, 14, 30, 60\}$:

$$\text{MSID}_t^T = \alpha + \sum_{k=1}^{4} \beta_k \, \text{MSID}_{t-k}^T + \sum_{k=0}^{4} \gamma_k \, \Delta\text{VIX}_{t-k} + \epsilon_t, \tag{4a}$$

$$\text{FSID}_{\text{agg},t}^T = \alpha + \sum_{k=1}^{4} \beta_k \, \text{FSID}_{\text{agg},t-k}^T + \sum_{k=0}^{4} \gamma_k \, \Delta\text{VIX}_{t-k} + \epsilon_t, \tag{4b}$$

In this specification, MSID_t^T ($\text{FSID}_{\text{agg},t}^T$) denotes the market-specific (firm-specific average) information demand at time t, based on a moving window of length T days. ΔVIX represents the first difference of the daily VIX values. Each regression includes four lags of both the dependent and independent variables to account for short-term persistence and potential dynamic feedback effects. Results are reported in Panel B of Table 4. For brevity, the coefficients and significance levels of the lagged dependent variables are omitted from the table but are available upon request.

The findings reveal a highly statistically significant positive relationship between ΔVIX and market-wide information demand (MSID), and a significant negative relationship between ΔVIX and firm-specific information demand (FSID_{agg}). The significance persists through the first lag across all metrics, with coefficient magnitudes that are similar in size. These results are consistent with the hypothesis that higher financial market uncertainty shifts limited investor attention toward broad market signals, thereby crowding out firm-specific information demand. The adjusted R^2 values reported in Panel B are also higher than those in Panel A, indicating that the inclusion of uncertainty measures improves the explanatory power of the regressions.

4.3 Information demand and stock price synchronicity

4.3.1 Metrics and descriptive statistics

Next, we examine the role of information demand in shaping stock price synchronicity by utilizing a synchronicity measure widely employed in the literature (Morck et al., 2000; Drake et al., 2017; Lin et al., 2019). Specifically, we first estimate the synchronicity of individual stock returns with market returns by running the following regression:

$$r_{i,t} = \alpha + \beta r_{mkt,t} + \epsilon_{i,t}, \tag{5}$$

where $r_{i,t}$ denotes the excess daily return of stock i at time t, and $r_{mkt,t}$ represents the value-weighted return on all NYSE, AMEX, and NASDAQ stocks (from CRSP) minus the risk-free rate. We estimate this regression separately for each firm and fiscal quarter, requiring a minimum of 45 trading day observations within each quarter. Specifically, we use data from the thirteen weeks preceding the fiscal quarter-end for each firm. Through the coefficient of determination from the regression for firm i in quarter t ($R^2_{i,t}$), stock return synchronicity is computed as:

$$\text{Synch}_{i,t} = \log\left(\frac{R^2_{i,t}}{1 - R^2_{i,t}}\right). \tag{6}$$

Building on this framework, we construct an analogous measure of information demand synchronicity. In this case, rather than regressing firm excess returns on market excess returns, we regress firm-specific information demand (FSID_i^T with i being a specific firm) on market-wide information demand (MSID^t). The key distinction is that the dependent and independent variables are based on information demand metrics rather than returns, allowing us to capture the extent to which firm-level information demand comoves with broader market-wide information acquisition patterns.

Table 5 presents the descriptive statistics for the synchronicity measures across both websites and all aggregation horizons (T). In addition to the synchronicity values, we also retain from each regression the estimated coefficients on market-wide information demand (β^T_{ID}) and market returns (β_{ret}). Consistent with our previous findings, the mean and median values of β^T_{ID} are negative across specifications, supporting the limited attention hypothesis and the substitutive relationship between firm-specific and market-wide information demand.

In contrast, the estimated coefficients on market returns, β_{ret}, are predominantly positive, with an average (median) value of 1.07 (1.00). For comparison, Drake et al. (2017) report an average annual return synchronicity of -4.19, suggesting a lower explanatory power of market returns for stock returns at lower frequencies. The stronger contemporaneous relationship we observe at the quarterly frequency is reasonable, as shorter horizons are likely to capture more immediate and transient dynamics between individual stock returns and broader market movements. It is important to note, however, that the information demand synchronicity measure developed in this study is not directly comparable to that employed by Drake et al. (2017), as we base our analysis on MSID rather than FSID_{agg}.

	Website 1			Website 2		
	Mean	Median	StDev	Mean	Median	StDev
Panel A: Information demand						
β^{7}_{ID}	-0.095	-0.097	0.912	-0.198	-0.176	0.884
β^{14}_{ID}	-0.120	-0.115	0.931	-0.199	-0.173	0.873
β^{30}_{ID}	-0.156	-0.142	1.104	-0.204	-0.167	1.014
β^{60}_{ID}	-0.119	-0.104	1.128	-0.196	-0.146	1.059
$\text{Synch}^{7}_{\text{ID}}$	-4.969	-4.514	2.223	-4.821	-4.340	2.234
$\text{Synch}^{14}_{\text{ID}}$	-4.757	-4.282	2.252	-4.534	-4.067	2.270
$\text{Synch}^{30}_{\text{ID}}$	-4.147	-3.701	2.270	-3.831	-3.375	2.237
$\text{Synch}^{60}_{\text{ID}}$	-4.025	-3.592	2.276	-3.729	-3.287	2.249
Panel B: Stock returns						
β_{ret}	1.075	1.019	0.618	1.050	1.001	0.630
$\text{Synch}_{\text{ret}}$	-1.591	-1.298	1.683	-1.748	-1.748	-1.748

This table reports summary statistics for the synchronicity measures calculated. Panel A contains the statistics for the β of the regression $\text{FSID}^{T}_{i,t} = \alpha + \beta \text{MSID}^{T}_{i,t} + \epsilon_t$ ($\beta^{T}_{\text{ID},i}$) and the synchronicity measure calculated ($\text{Synch}^{T}_{\text{ID}}$). Panel B contains the statistics for the β of the regression $r_t = \alpha + \beta r_{mkt,t} + \epsilon_t$ (β_{ret}) and the synchronicity measure calculated ($\text{Synch}_{\text{ret}}$).

Table 5: Descriptive statistics of the synchronicity measures.

4.3.2 Determinants of synchronicity

We estimate contemporaneous regressions to examine whether and how information demand synchronicity is associated with stock price synchronicity. In addition, we construct a dummy variable, PositiveID_t, that equals 1 if $\beta_{\text{ID},t} > 0$ and 0 otherwise[13]. We estimate the following baseline specifications:

$$\text{Synch}_{\text{ret},t} = \alpha + \beta_1 \,\text{Synch}_{\text{ID},t} + \beta_2 \,\text{PositiveID}_t + \beta_3 \,(\text{PositiveID}_t \times \text{Synch}_{\text{ID},t}) + \epsilon_t, \tag{7a}$$

$$\text{Synch}_{\text{ID},t} = \alpha + \beta_1 \,\text{Synch}_{\text{ret},t} + \beta_2 \,\text{PositiveID}_t + \beta_3 \,(\text{PositiveID}_t \times \text{Synch}_{\text{ret},t}) + \epsilon_t, \tag{7b}$$

where $\text{Synch}_{\text{ret},t}$ denotes stock return synchronicity at time t, $\text{Synch}_{\text{ID},t}$ represents information demand synchronicity at the same time period, PositiveID_t is the dummy variable indicating when MSID and FSID are positively related and $(\text{PositiveID}_t \times \text{Synch}_{\text{ID},t})$ is the interaction term. The combined effect of the information demand synchronicity and the interaction term is also estimated.

[13] We use $\beta_{\text{ID},t} < 0$ as the default case because most of the observations have a negative coefficient. The results remain when we reverse the effect.

In these specifications, β_1 captures the marginal effect of information demand synchronicity on stock return synchronicity when $\text{PositiveID}_t = 0$, that is, when $\beta_{\text{ID},t} \leq 0$. The coefficient β_2 captures the shift in the intercept associated with periods when $\text{PositiveID}_t = 1$, while β_3 captures the change in the slope of information demand synchronicity under $\text{PositiveID}_t = 1$. Thus, the total effect of information demand synchronicity on stock return synchronicity when $\text{PositiveID}_t = 1$ is given by the sum $\beta_1 + \beta_3$. We estimate and report both the baseline coefficients and the combined effect, and test the significance of the combined effect using a Wald test. We estimate this model with and without additional control variables, to account for other determinants of stock price synchronicity.

In the specifications including controls, we add all the quarterly firm characteristics described in Section 3 to account for other factors that may influence stock price or information demand synchronicity. All the regressions include fixed-year effects, which also account for the COVID period, as well as month-of-the-year effects to account for seasonality effects. Standard errors are clustered at the firm level. Table 6 provides the results for the regression model specified in Equation 7a, for Websites 1 and 2 and $T \in \{7, 60\}$. For brevity only these results are presented, however, the main findings remain when using the metrics for $T \in \{14, 30\}$, and when keeping only the subset of firm-quarter pairs where β_{ID} is significant at a 10% significance level.

Our findings provide strong support for *Hypotheses H3* and *H4*, revealing two distinct effects of information demand on stock return synchronicity. First, when β_{ID} is negative, indicating a substitution between market-wide and firm-specific information demand, we find that higher (lower) information demand synchronicity is associated with higher (lower) stock return synchronicity. This pattern is consistent with the notion that, due to limited attention capacity, investors shift their focus toward market-wide signals during periods of heightened market uncertainty. The resulting decline in firm-specific information acquisition induces more correlated trading across individual stocks, thereby increasing the observed synchronicity between stock and market returns. In contrast, during periods characterized by greater firm-specific uncertainty, investors allocate more attention to idiosyncratic firm information, leading to lower information demand synchronicity. This reallocation of attention reduces the collective trading of stocks based on common signals, resulting in lower stock return synchronicity.

The effects reverse when β_{ID} is positive, indicating a spillover between market-wide and firm-specific information demand. In this regime, an increase in MSID appears to induce a corresponding increase in FSID, leading to higher information demand synchronicity and lower stock return synchronicity, as more firm-specific information is incorporated into stock prices. This mechanism resembles the "attention enhancement" effect documented

	Website 1				Website 2			
	$Synch^{7}_{ret}$		$Synch^{60}_{ret}$		$Synch^{7}_{ret}$		$Synch^{60}_{ret}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	-1.361***	-3.992***	-1.361***	-4.044***	-1.260***	-4.164***	-1.260***	-4.194***
	(0.086)	(0.127)	(0.086)	(0.127)	(0.090)	(0.132)	(0.090)	(0.132)
$Synch_{ID}$	0.019***	0.015***	0.019***	0.008*	0.034***	0.033***	0.034***	0.018***
	(0.005)	(0.004)	(0.005)	(0.004)	(0.005)	(0.004)	(0.005)	(0.004)
$Positive_{ID}$	-0.235***	-0.257***	-0.235***	-0.392***	-0.331***	-0.422***	-0.331***	-0.467***
	(0.042)	(0.037)	(0.042)	(0.037)	(0.045)	(0.039)	(0.045)	(0.039)
$Positive_{ID} \times Synch_{ID}$	-0.031***	-0.033***	-0.031***	-0.060***	-0.043***	-0.054***	-0.043***	-0.064***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.007)	(0.008)	(0.007)
ln(MktCap)		0.253***		0.254***		0.285***		0.286***
		(0.015)		(0.015)		(0.016)		(0.016)
ROA		0.807***		0.812***		0.799***		0.795***
		(0.261)		(0.261)		(0.268)		(0.268)
BKMkt		0.075***		0.078***		0.092***		0.097***
		(0.027)		(0.027)		(0.028)		(0.028)
Sales		-0.101***		-0.098***		-0.101***		-0.066***
		(0.017)		(0.017)		(0.019)		(0.019)
StdROA		-2.980***		-3.007***		-2.503***		-2.511***
		(0.356)		(0.356)		(0.358)		(0.358)
Price		-0.001**		0.000**		-0.001***		-0.001**
		(0.000)		(0.000)		(0.000)		(0.000)
IO		1.046***		1.043***		1.175***		1.153***
		(0.074)		(0.074)		(0.072)		(0.072)
# Analysts		-0.004**		-0.004*		-0.007***		-0.007***
		(0.002)		(0.002)		(0.002)		(0.002)
Tobin's Q		-0.011		-0.010		-0.010		-0.009
		(0.007)		(0.007)		(0.007)		(0.007)
Combined effect	-0.012**	-0.018***	-0.043***	-0.052***	-0.009	-0.021***	-0.024***	-0.046***
	(0.006)	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)
N. obs.	45835	45835	45763	45763	44021	44021	41842	41842
Adjusted R^2	0.074	0.197	0.078	0.201	0.061	0.206	0.063	0.210
FE year	Y	Y	Y	Y	Y	Y	Y	Y
FE month-of-the-year	Y	Y	Y	Y	Y	Y	Y	Y

This table presents panel regression results analyzing the relationship between stock return synchronicity ($Synch_{\text{ret}}$) and information demand synchronicity ($Synch_{\text{ID}}$) for the two websites analyzed in this study. Regressions include fixed year and month-of-the-year effects and cluster standard errors at the firm level. Results are shown for $FSID^{7}$ and $FSID^{60}$, but the results remain for all the measures utilized in the study. Significance levels are indicated by *, **, and *** for 10%, 5%, and 1% levels, respectively.

Table 6: Contemporaneous regressions of the synchronicity measures.

in the literature for institutional investors (Sheng and Hirshleifer, 2022; Liu et al., 2022), whereby the arrival of macroeconomic news increases overall investor attention rather than reallocating it. As the increase in FSID is less explained by increases in MSID, this may indicate firm-specific uncertainty that causes wait-and-see effects at the firm level, leading to temporary synchronicity in the returns.

In contrast to the existing literature, we find that when a decrease in FSID is driven by a decline in MSID, stock return synchronicity also decreases. More specifically, Lin et al. (2019) study exogenous distraction events and document that when investors' attention is diverted away from the market, stock return synchronicity increases. They argue that exogenous distractions limit the attention allocated to firm-specific information, leading investors to rely more heavily on market-wide signals and thus trade in a more correlated manner. However, our findings suggest that when the distraction reduces overall attention, both to MSID and FSID, the coordinating effect among investors weakens, resulting in lower stock return synchronicity. In this case, stock prices reflect a greater degree of idiosyncratic noise, as investors are less able to collectively respond to common information signals.

Prior studies argue that institutional investors, due to their greater experience and information-processing abilities, are more likely to exhibit attention enhancement following macroeconomic news releases (Liu et al., 2022; Sheng and Hirshleifer, 2022). In contrast, our findings suggest that similar dynamics also arise among retail investors. We show that both the crowding-out effect and the attention enhancement effect are present in retail investor behavior, although the prevalence of each mechanism appears to vary across firms and financial market conditions.

The coefficients on the control variables are broadly consistent with those reported by Drake et al. (2017). Higher stock return synchronicity is associated with larger firms, as well as firms with higher return on assets (ROA), higher book-to-market ratios, and greater institutional ownership. Conversely, firms with higher sales growth, higher stock price, higher Tobin's Q, higher standard deviation of ROA, and more analysts following the firm exhibit lower synchronicity. These patterns are consistent with the notion that larger, more mature firms with stronger institutional presence and less private information uncertainty tend to have stock prices that move more closely with market-wide factors.

To address concerns of endogeneity, specifically reverse causality, we also conduct regressions where the information demand synchronicity metrics are the dependent variables, and the return synchronicity metrics are the independent variables (Table 7). While our hypotheses suggest that information demand synchronicity influences return synchronicity, these additional regressions help explore whether there might be any significant feedback effects in the opposite direction. The adjusted R^2 values from these regressions appear relatively small, indicating that return synchronicity explains very little of the variation in information demand synchronicity. This finding provides evidence against substantial reverse causality concerns. The low explanatory power of these models suggests that the relationship mainly holds in the hypothesized direction, where shifts in information demand synchronicity drive changes in return synchronicity rather than the reverse.

In addition to these results, we find that certain firm characteristics are associated with information demand synchronicity, offering insight into the determinants of coordinated information acquisition. Similar to the patterns observed for stock return synchronicity, information demand synchronicity is higher for larger firms, consistent with the idea that size enhances firm visibility and attracts broader investor attention. However, we observe notable differences as well. Information demand synchronicity is negatively related to the book-to-market ratio, the standard deviation of ROA, the number of analysts following the firm, and Tobin's Q. These patterns suggest that firms characterized by greater growth opportunities (lower book-to-market, higher Tobin's Q), more analyst coverage, and more volatile fundamentals attract more idiosyncratic — and less coordinated — information demand. In such settings, investors appear to seek more firm-specific signals, reducing the comovement in information acquisition patterns across firms.

4.4 Information demand jumps and stock price synchronicity

Numerous studies have investigated the impact of external events on investor attention. For instance, Lin et al. (2019) focus on large jackpot days, while Sheng and Hirshleifer (2022) and Liu et al. (2022) examine dual announcement days—periods when both firm-specific and market-specific announcements occur. This body of literature consistently demonstrates that retail investors tend to redirect their attention toward market-wide occurrences, reducing firm-specific information demand during such events. This reallocation of attention has been linked to asset price anomalies, highlighting the broader implications of investor distraction.

Our study diverges from this traditional approach by aiming to isolate the effects of attention allocation independently of the nature of the triggering event. Rather than relying on specific external events as proxies for attention distraction, we identify shocks in attention allocation directly and evaluate their influence on stock price synchronicity. To achieve this, we leverage established methodologies from the literature on jump detection in time series processes. By doing so, we provide evidence of how shifts in attention allocation contribute to price comovement, offering a novel perspective on the dynamic relationship between information processing and market outcomes.

Information demand jumps are identified using a non-parametric approach (Lee and Mykland, 2008). To identify jumps, we use the normal distribution from Lee and Mykland (2008) to determine jump thresholds. We observe the jumps for the 99^{th}, 95^{th}, and 90^{th} percentiles of the normal distribution and the results remain for all these thresholds. We use K=16 as the observations are daily, but the results remain consistent for different values of K. We detect jumps both for MSID and each firm's FSID.

First, for each firm i in our sample, we calculate the correlation between the stock's excess

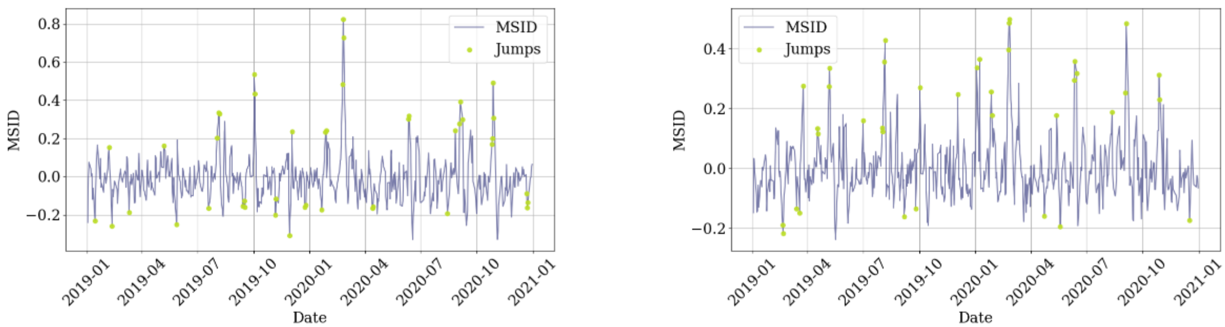
	Website 1				Website 2			
	$\text{Synch}^{7}_{\text{ID}}$		$\text{Synch}^{60}_{\text{ID}}$		$\text{Synch}^{7}_{\text{ID}}$		$\text{Synch}^{60}_{\text{ID}}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	-4.510***	-4.920***	-4.648***	-4.501***	-4.313***	-4.570***	-4.385***	-4.206***
	(0.076)	(0.117)	(0.078)	(0.118)	(0.080)	(0.114)	(0.083)	(0.121)
Synch_{ret}	0.023***	0.030***	0.039***	0.000	0.051***	0.050***	0.058***	0.007
	(0.009)	(0.009)	(0.010)	(0.010)	(0.008)	(0.009)	(0.008)	(0.009)
$\text{Positive}_{\text{ID}}$	-0.396***	-0.304***	-0.301***	-0.387***	-0.675***	-0.636***	-0.643***	-0.504***
	(0.031)	(0.031)	(0.032)	(0.031)	(0.034)	(0.033)	(0.034)	(0.034)
$\text{Positive}_{\text{ID}} \times \text{Synch}_{\text{ID}}$	-0.074***	-0.065***	-0.063***	-0.098***	-0.087***	-0.070***	-0.070***	-0.068***
	(0.013)	(0.013)	(0.014)	(0.014)	(0.013)	(0.013)	(0.014)	(0.014)
ln(MktCap)		0.028***		0.062***		0.002		0.045***
		(0.011)		(0.010)		(0.011)		(0.012)
ROA		-0.008		-0.323		-0.091		-0.641**
		(0.261)		(0.256)		(0.271)		(0.271)
BKMkt		-0.028		-0.047*		-0.034		-0.005
		(0.026)		(0.025)		(0.026)		(0.028)
Sales		0.009		-0.019		-0.020		0.011
		(0.024)		(0.024)		(0.024)		(0.027)
StdROA		0.771**		2.088***		1.628***		1.916***
		(0.385)		(0.390)		(0.380)		(0.391)
Price		0.000*		0.000***		0.000**		-0.001***
		(0.000)		(0.000)		(0.000)		(0.000)
IO		-0.069		-0.090		0.045		0.077
		(0.056)		(0.055)		(0.053)		(0.053)
# Analysts		0.004**		0.009***		0.007***		0.011***
		(0.002)		(0.002)		(0.002)		(0.002)
Tobin's Q		0.013**		0.028***		0.020***		0.021***
		(0.007)		(0.006)		(0.006)		(0.006)
Combined effect	-0.051**	-0.034***	-0.024***	-0.098***	-0.013	-0.020*	-0.037***	-0.061***
	(0.010)	(0.010)	(0.011)	(0.011)	(0.010)	(0.010)	(0.011)	(0.011)
N. obs.	45835	45835	45763	45763	44021	44021	41842	41842
Adjusted R^2	0.020	0.027	0.015	0.021	0.019	0.025	0.017	0.023
FE year	Y	Y	Y	Y	Y	Y	Y	Y
FE month-of-the-year	Y	Y	Y	Y	Y	Y	Y	Y

This table presents panel regression results analyzing the relationship between information demand synchronicity ($Synch_{\text{ID}}$) and stock return synchronicity ($Synch_{\text{ret}}$) for the two websites analyzed in this study. Regressions include fixed year and month-of-the-year effects and cluster standard errors at the firm level. Results are shown for FSID^7 and FSID^{60}, but the results remain for all the measures utilized in the study. Significance levels are indicated by *, **, and *** for 10%, 5%, and 1% levels, respectively.

Table 7: Contemporaneous regressions of the synchronicity measures (continued).

return and the market excess return separately for days classified as jump days ($Corr_i^j$) and non-jump days ($Corr_i^{nj}$). We use only the firms with more than 20 identified jumps. Second, we estimate the adjusted R^2 from the following regression, separately for jump and non-jump days:

$$r_{i,t} = \alpha + \beta\, r_{mkt,t} + \epsilon_{i,t}, \tag{8}$$



(a) Website 1

(b) Website 2

The jumps shown are calculated for $T = 7$ and the market-specific information demand (MSID). They are based on the 95^{th} percentile of the normal distribution, for K=16, following (Lee and Mykland, 2008). The period between January 2019 to December 2020 is shown for both websites.

Figure 7: Jumps detected on MSID.

where $r_{i,t}$ is the excess return of firm i at time t, and $r_{mkt,t}$ is the excess market return. We denote the resulting adjusted R^2 for jump and non-jump days as $R^2_{j,i}$ and $R^2_{nj,i}$, respectively. For both the correlation and adjusted R^2 measures, we compute the mean and median of two comparisons across firms: the absolute difference and the percentage change between jump and non-jump days, as defined by:

$$\text{Diff} = x_i^j - x_i^{nj}, \qquad \text{Pct.Ch.} = \frac{x_i^j - x_i^{nj}}{x_i^{nj}}. \tag{9}$$

The percentage change results are winsorized at the 1st and 99th percentiles to mitigate the influence of outliers in the median calculations. Statistical significance is assessed using paired t-tests for means and Wilcoxon signed-rank tests for medians. This methodology is similar in spirit to Lin et al. (2019), who study the effects of exogenous distractions on stock return comovement. However, to the best of our knowledge, we are the first to apply a jump detection framework to information demand metrics, allowing for a novel analysis of attention shifts at the intraday level.

To test for the effects of market-wide and firm-specific information demand jumps we employ an intuitive methodology. We calculate the metrics described and the necessary statistics for four cases (a) when there is a positive market-wide information demand jump; (b) when there is a negative market-wide information demand jump; (c) when there is a positive firm-specific information demand jump; (a) when there is a negative firm-specific information demand jump. For each of these cases we compare the correlation and the adjusted R^2 between the days that include a jump and the days that do not include a jump for the respective measure (MSID or FSID). The descriptive statistics of the jumps identified are provided in Table 8. The results on the correlation metrics for the 95^{th} percentile and time horizon T are reported in Table 9. For this analysis we keep only the firms with at least 20 jumps of the specific type. Note that the results are consistent and significant for all the horizons T.

		Website 1			Website 2		
		All	Positive	Negative	All	Positive	Negative
MSID	N. jumps	99	62	37	89	58	31
FSID	Mean	97.9	67.3	30.6	84.3	55.0	29.3
	25%	88.0	57.0	22.0	73.0	43.0	19.0
	50%	103.0	70.0	30.0	93.0	58.0	28.0
	75%	114.0	82.0	38.0	101.0	69.0	38.0

This table provides the descriptive statistics of the jumps identified for $T = 7$ and the 95^{th} percentile of the normal distribution.

Table 8: Descriptive statistics of jumps.

The jump analysis largely corroborates the patterns observed in our synchronicity analysis. We find that positive (negative) jumps in MSID are associated with higher (lower) stock return synchronicity. This finding is consistent with the mechanism whereby, when $\beta_{\text{ID}} < 0$, an increase in MSID crowds out FSID, leading to a rise in return synchronicity as investors collectively respond to common market-wide signals. Conversely, when $\beta_{\text{ID}} > 0$ and MSID decreases, the simultaneous decline in FSID suggests a broad distraction from both market-wide and firm-specific information, resulting in greater noise in stock prices and reduced synchronicity.

Turning to FSID jumps, we observe that positive (negative) FSID jumps are associated with lower (higher) stock return synchronicity. These results are again consistent with the theoretical mechanisms outlined earlier. When $\beta_{\text{ID}} < 0$ and FSID increases, coordinated information acquisition weakens, and there is more firm-specific information incorporated in prices, thereby lowering synchronicity. When $\beta_{\text{ID}} > 0$ and FSID increases alongside MSID, the resulting increase in information demand synchronicity reflects greater overall information incorporation at the firm level, which reduces return comovement through the spillover mechanism.

Conceptually, a positive MSID jump could either increase stock return synchronicity if $\beta_{\text{ID}} < 0$ due to the crowding-out effect, or decrease synchronicity if $\beta_{\text{ID}} > 0$ due to the spillover mechanism. To address potential concerns arising from this dual interpretation, we further identify simultaneous jumps in both MSID and FSID and conduct the analysis based on combinations of positive and negative jumps. Specifically, we define jumps based on the 75^{th} percentile of the normal distribution for each metric, ensuring a sufficient number of simultaneous jump events across firms. Using this approach, we find that periods characterized by simultaneous positive jumps in MSID and FSID are associated with lower stock return synchronicity. This result is consistent with the spillover mechanism, where increased attention to both market-wide and firm-specific information reduces comovement by enhancing firm-specific information incorporation into stock prices. The results are reported at Panel C of Table 9.

4.5 Determinants of information demand comovement

To examine the firm-level determinants of the probability that the relationship between MSID and FSID is negative ($\beta_{\text{ID}} < 0$), we estimate logistic regression models. Specifically, we model the probability that the binary outcome variable equals one as:

$$\Pr(y_{it} = 1 \mid X_{it}) = F(\alpha + X_{it}'\gamma + \mu_t + \epsilon_{it}),$$

where y_{it} is an indicator variable equal to 1 if $\beta_{\text{ID},it} < 0$ and 0 otherwise, X_{it} represents a vector of firm characteristics and uncertainty variables, μ_t denotes year and month-of-the-year fixed effects to capture time specific effects, $F(\cdot)$ is the logistic cumulative distribution function, and ϵ_{it} is the idiosyncratic error term. Standard errors are clustered at the firm level to account for potential within-firm serial correlation. Note that for the uncertainty variables we use the first difference of the 3-month averages of each metric because they are highly persistent. For VIX we also first average the index at the monthly level, and then treat it as the rest of the uncertainty indices.

The results are reported in Tables 10 and 11 for $T = 7$ and $T = 60$ respectively. The results of the logistic regression reveal several characteristics of the firm that significantly influence the likelihood of observing a negative relationship between MSID and FSID ($\beta_{\text{ID}} < 0$). Larger firms and firms with higher book-to-market ratios are less likely to experience substitution between market-wide and firm-specific information demand. This is consistent with the greater visibility of such firms, as well as the fact that retail investors are known to focus on attention-grabbing stocks (Boehmer et al., 2021). At the same time, when uncertainty is higher, the focus of investors may shift to perceived "safer assets" (Garlappi et al., 2007; Dimmock et al., 2016; Peijnenburg, 2018; Kostopoulos et al., 2022).

In contrast, firms with greater fundamental volatility (higher standard deviation of ROA), higher Tobin's Q, and greater institutional ownership exhibit a higher probability of $\beta_{\text{ID}} < 0$, suggesting that growth-oriented and institutionally held firms are more vulnerable to attention reallocations favoring market-wide signals. This aligns with *Hypothesis 5*, that the attention distraction will be higher for lower retail ownership stocks, while retail investors will search for more information for assets they may already hold.

Furthermore, periods of heightened uncertainty, as captured by increases in the VIX and Ludvigson et al. (2015) indices, are associated with a higher likelihood of negative β_{ID}, supporting the view that attention constraints intensify during times of elevated macroeconomic risk. This is in line with *Hypotheses 1* and *2* that refer to relationship between MSID and aggregated FSID. We find a postive relationship between all the uncertainty indices utilised in this study, for all the different time horizons T used to construct the information demand metrics.

		Website 1				Website 2			
		Jump	No jump	Difference	Percentage	Jump	No jump	Difference	Percentage
Panel A: Market specific information demand (MSID)									
All jumps (1)									
Correlation	Mean	0.502	0.468	0.034***	0.094***	0.496	0.455	0.041***	0.123***
	Median	0.530	0.486	0.040***	0.077***	0.528	0.474	0.044***	0.085***
Adj. R^2	Mean	0.275	0.243	0.033***	0.241***	0.268	0.233	0.036***	0.290***
	Median	0.271	0.235	0.028***	0.119***	0.267	0.224	0.028***	0.122***
Positive jumps (2)									
Correlation	Mean	0.544	0.478	0.066***	0.166***	0.549	0.473	0.076***	0.199***
	Median	0.583	0.493	0.077***	0.142***	0.588	0.490	0.081***	0.158***
Adj. R^2	Mean	0.318	0.250	0.068***	0.404***	0.322	0.247	0.075***	0.517***
	Median	0.326	0.242	0.071***	0.256***	0.333	0.240	0.072***	0.282***
Negative jumps (3)									
Correlation	Mean	0.379	0.499	-0.121***	-0.254***	0.354	0.508	-0.154***	-0.311***
	Median	0.402	0.515	-0.106***	-0.207***	0.380	0.522	-0.144***	-0.273***
Adj. R^2	Mean	0.168	0.269	-0.101***	-0.419***	0.138	0.277	-0.139***	-0.538***
	Median	0.136	0.264	-0.105***	-0.479***	0.110	0.272	-0.146***	-0.589***
Panel B: Firm specific information demand (FSID)									
All jumps (1)									
Correlation	Mean	0.336	0.499	-0.164***	-0.339***	0.298	0.497	-0.200***	-0.411***
	Median	0.345	0.518	-0.166***	-0.329***	0.299	0.519	-0.202***	-0.405***
Adj. R^2	Mean	0.140	0.273	-0.132***	-0.495***	0.115	0.272	-0.157***	-0.585***
	Median	0.109	0.268	-0.133***	-0.593***	0.077	0.269	-0.159***	-0.707***
Positive jumps (2)									
Correlation	Mean	0.306	0.506	-0.201***	-0.406***	0.262	0.507	-0.245***	-0.490***
	Median	0.307	0.522	-0.204***	-0.400***	0.260	0.528	-0.250***	-0.488***
Adj. R^2	Mean	0.120	0.279	-0.159***	-0.586***	0.093	0.281	-0.187***	-0.678***
	Median	0.082	0.272	-0.159***	-0.707***	0.050	0.279	-0.192***	-0.813***
Negative jumps (3)									
Correlation	Mean	0.574	0.545	0.029***	0.068***	0.567	0.540	0.027***	0.064***
	Median	0.602	0.553	0.042***	0.072***	0.600	0.555	0.037***	0.062***
Adj. R^2	Mean	0.349	0.313	0.035***	0.171***	0.347	0.311	0.036***	0.189***
	Median	0.341	0.305	0.027***	0.090***	0.341	0.308	0.024***	0.072***
Panel C: Simultaneous firm specific (FSID) and market-specific (MSID) information demand jumps									
Positive FSID - Positive MSID (1)									
Correlation	Mean	0.449	0.556	-0.107***	-0.199***	0.440	0.567	-0.128***	-0.226***
	Median	0.478	0.566	-0.086***	-0.149***	0.468	0.577	-0.111***	-0.189***
Adj. R^2	Mean	0.224	0.326	-0.102***	-0.336***	0.213	0.341	-0.128***	-0.369***
	Median	0.195	0.319	-0.115***	-0.373***	0.182	0.333	-0.135***	-0.445***

This table presents the mean and median values of the absolute difference ($Diff = x_i^j - x_i^{nj}$) and the percentage change ($Pct.Ch. = \frac{x_i^j - x_i^{nj}}{x_i^{nj}}$) in correlations between days with a jump (x_i^j) and days without a jump (x_i^{nj}) for each firm i. The percentage change values are winsorized at the 1% and 99% levels to mitigate the influence of outliers. The reported significance levels for the mean and median differences are based on a paired t-test and Wilcoxon signed-rank test, respectively. In Panel A (Panel B) jumps are identified based on MSID^7 (FSID^7). The table further breaks down the analysis into four cases: Panel A (1) all market-wide information demand jumps, Panel A (2) positive market-wide information demand jumps, Panel A (3) negative market-wide information demand jumps, Panel B (1) all firm-specific information demand jumps, Panel B (2) positive firm-specific information demand jumps, Panel B (3) negative firm-specific information demand jumps. For each case, the correlations ($Corr$) are computed separately for days with and without the specified type of jump. Results are presented for jumps identified at the 95^{th} percentile of the normal distribution, with K=16. Panel C includes the statistics for simultaneous positive jumps identified at the 75^{th} percentile of the normal distribution.

Table 9: Attention allocation jumps and returns' synchronicity.

	Website 1						Website 2					
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.221	0.172	0.192	0.107	0.129	0.138	0.751	0.730***	0.758***	0.678***	0.745***	0.722***
	(2.341)	(0.214)	(0.216)	(0.216)	(0.215)	(0.215)	(1.622)	(0.215)	(0.211)	(0.212)	(0.212)	(0.212)
ln(MktCap)	-0.029***	-0.027***	-0.028***	-0.028***	-0.028***	-0.029***	-0.070***	-0.066***	-0.066***	-0.067***	-0.066***	-0.067***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
ROA	0.259	0.310	0.341	0.276	0.282	0.273	0.088	0.077	0.112	0.075	0.098	0.088
	(0.241)	(0.240)	(0.240)	(0.240)	(0.240)	(0.240)	(0.271)	(0.269)	(0.270)	(0.269)	(0.269)	(0.269)
BkMkt	-0.068***	-0.075***	-0.073***	-0.070***	-0.068***	-0.066***	-0.179***	-0.178***	-0.178***	-0.174***	-0.174***	-0.170***
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.027)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)
Sales	0.034	0.036	0.040*	0.036	0.042*	0.039*	-0.033	-0.038*	-0.035	-0.038*	-0.027	-0.030
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
StdROA	0.617*	0.670**	0.637*	0.635*	0.599*	0.625*	1.543***	1.573***	1.583***	1.537***	1.574***	1.544***
	(0.335)	(0.335)	(0.335)	(0.335)	(0.334)	(0.335)	(0.383)	(0.378)	(0.378)	(0.377)	(0.377)	(0.377)
Price	-0.001***	0.000***	0.000***	0.000***	0.000***	0.000***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
IO	0.310***	0.308***	0.308***	0.310***	0.309***	0.311***	0.312***	0.306***	0.306***	0.308***	0.306***	0.308***
	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)	(0.053)	(0.053)	(0.053)	(0.053)	(0.053)	(0.053)
# Analysts	-0.001	-0.002	-0.002	-0.002	-0.002	-0.002	0.005***	0.004**	0.004**	0.004**	0.004**	0.004**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Tobin's Q	0.028***	0.028***	0.028***	0.028***	0.028***	0.028***	0.030***	0.027***	0.028***	0.027***	0.028***	0.028***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
ΔVIX$_{avg}$		0.023***						0.026***				
		(0.003)						(0.003)				
ΔEPU$_{avg}$			0.003***						0.004***			
			(0.000)						(0.000)			
ΔLD-Financial$_{avg}$				1.413***						2.314***		
				(0.256)						(0.281)		
ΔLD-Real$_{avg}$					0.920***						2.232***	
					(0.304)						(0.322)	
ΔLD-Macro$_{avg}$						0.302						1.127***
						(0.257)						(0.265)
N. obs.	45835	45835	45835	45835	45835	45835	44021	44021	44021	44021	44021	44021
Pseudo R^2	0.005	0.004	0.004	0.004	0.003	0.003	0.019	0.012	0.012	0.012	0.012	0.011
FE year	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
FE month-of-the-year	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

This table presents logistic regression results analyzing the determinants of the negative relationship between FSID and MSID or else $\beta_{\mathrm{ID}} < 0$. Regressions include fixed year and month-of-the-year effects and cluster standard errors at the firm level. Results are shown for β^7_{ID}, but the results remain for all the measures utilized in the study. Significance levels are indicated by *, **, and *** for 10%, 5%, and 1% levels, respectively.

Table 10: Determinants of negative β^7_{ID}

Table 11: Determinants of negative β_{ID}^{60}

	Website 1						Website 2					
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.205	0.408*	0.398*	0.346	0.351	0.338	0.715	1.177***	1.224***	1.148***	1.178***	1.170***
	(2.234)	(0.214)	(0.217)	(0.217)	(0.217)	(0.217)	(1.711)	(0.209)	(0.206)	(0.208)	(0.207)	(0.207)
ln(MktCap)	-0.014	-0.013	-0.013	-0.014	-0.013	-0.012	-0.066***	-0.066***	-0.065***	-0.066***	-0.065***	-0.065***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
ROA	-0.317	-0.372	-0.319	-0.399*	-0.334	-0.313	0.012	-0.160	-0.082	-0.172	-0.076	-0.049
	(0.244)	(0.243)	(0.244)	(0.242)	(0.243)	(0.243)	(0.267)	(0.262)	(0.263)	(0.262)	(0.263)	(0.263)
BkMkt	-0.101***	-0.095***	-0.098***	-0.088***	-0.094***	-0.096***	-0.185***	-0.168***	-0.177***	-0.167***	-0.176***	-0.175***
	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.027)	(0.026)	(0.027)	(0.026)	(0.027)	(0.027)
Sales	-0.004	-0.002	0.005	-0.002	0.014	0.020	-0.063***	-0.060**	-0.056**	-0.059**	-0.044*	-0.042*
	(0.023)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.023)	(0.024)	(0.023)	(0.024)	(0.023)	(0.023)
StdROA	0.589	0.607	0.622*	0.607	0.599	0.587	0.758**	0.785**	0.831**	0.761**	0.790**	0.797**
	(0.372)	(0.370)	(0.370)	(0.369)	(0.369)	(0.370)	(0.380)	(0.374)	(0.374)	(0.374)	(0.373)	(0.374)
Price	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
IO	0.202***	0.208***	0.206***	0.211***	0.207***	0.205***	0.240***	0.240***	0.236***	0.241***	0.235***	0.236***
	(0.050)	(0.050)	(0.050)	(0.049)	(0.050)	(0.050)	(0.052)	(0.051)	(0.051)	(0.051)	(0.051)	(0.051)
# Analysts	-0.002	-0.003	-0.003	-0.002	-0.003	-0.003	0.000	0.001	0.000	0.001	0.000	0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Tobin's Q	0.024***	0.020***	0.020***	0.020***	0.020***	0.020***	0.041***	0.035***	0.035***	0.035***	0.035***	0.035***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
ΔVIX$_{avg}$		0.023***						0.012***				
		(0.003)						(0.003)				
ΔEPU$_{avg}$			0.006***						0.005***			
			(0.000)						(0.000)			
ΔLD-Financial$_{avg}$				1.093***						1.239***		
				(0.243)						(0.262)		
ΔLD-Real$_{avg}$					2.812***						3.389***	
					(0.300)						(0.300)	
ΔLD-Macro$_{avg}$						2.903***						3.006***
						(0.254)						(0.253)
N. obs.	45763	45762	45763	45763	45763	45763	41842	41841	41842	41842	41842	41842
Pseudo R^2	0.013	0.008	0.009	0.007	0.008	0.008	0.028	0.018	0.020	0.018	0.020	0.020
FE year	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
FE month-of-the-year	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

This table presents logistic regression results analyzing the determinants of the negative relationship between FSID and MSID or else $\beta_{\text{ID}} < 0$. Regressions include fixed year and month-of-the-year effects and cluster standard errors at the firm level. Results are shown for β_{ID}^{60}, but the results remain for all the measures utilized in the study. Significance levels are indicated by *, **, and *** for 10%, 5%, and 1% levels, respectively.

5 Conclusion

This paper identifies and explores the full range of interactions between market-specific and firm-specific information demand (MSID and FSID, respectively) that can either increase or reduce the synchronicity of stock returns. By doing so, we offer novel evidence on the dynamics of information demand synchronicity regimes and the factors that shape them.

Our findings reveal a generally negative relationship between MSID and FSID, consistent with existing theoretical models. We show that MSID and FSID function as substitutes, and that both are closely tied to market uncertainty. In particular, daily uncertainty, proxied by the VIX, increases the market-specific focus while reducing firm-specific information demand, in line with theories of limited investor attention and coordination.

While the substitution effect generally holds, it does not universally apply when considering the relationship between market-wide attention and information demand for specific firms. We demonstrate that when MSID and FSID are negatively related, a higher synchronicity in information demand is associated with higher stock return synchronicity, supporting the attention crowding-out hypothesis. At the same time, greater FSID reduces both information demand synchronicity and stock return synchronicity, as more idiosyncratic information becomes incorporated into prices.

Prior literature attributes the attention distraction primarily to retail investors, while institutional investors are shown to exhibit the opposite pattern when exposed to both macro and micro-level news. Importantly, our findings indicate that both mechanisms can coexist within the same investor type. When MSID and FSID are positively related, information demand synchronicity becomes negatively associated with stock return synchronicity. In this spillover mechanism, increased synchronicity between market and firm-specific attention amplifies the firm-specific signal, thereby reducing stock return synchronicity with the broader market. Conversely, when information demand synchronicity is low, the market-wide signal tends to dominate, leading to increased stock return synchronicity.

These results are justified through using click-by-click activity on two separate retail investors' websites and using subsets of the firms based on the significance of the coefficient in the synchronicity regression. In addition, we employ a novel jumps methodology to identify positive and negative information demand jumps to further justify our hypotheses.

Finally, we investigate the determinants of the attention crowding-out and spillover effects. We show that retail investor attention will be crowded out for firms with higher institutional ownership, Tobin's Q, and fundamentals' volatility, whereas the spillover effect is more prominent for larger firms with larger fundamentals and higher retail ownership. These findings provide a unique explanation to the different attention interaction regimes.

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