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Informed trading, investor beliefs consensus and volatility: Evidence from the Limit Order Book dynamics during COVID-19 and short-selling ban

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A B S T R A C T

This study investigates the relationship between short-horizon volatility and two distinct sources of microstructural information: executed order flow, measured by VPIN, and the latent order book structure, proxied by its SLOPE. While VPIN captures the realized trade imbalances, SLOPE acts as a proxy for aggregated "belief consensus." The objective is to systematically compare the relative importance of these mechanisms—realized flow versus latent consensus—as drivers and predictors of market volatility. Using tick-by-tick data and the full limit order book for 32 IBEX-35 constituents during the 2019–2020 period, we employ a multifaceted econometric approach in event-time (volume clock), combining stock-level regressions with random-effects meta-analysis, robust fixed-effects panels (Driscoll–Kraay), conditional-probability tables (CPTs), and stock-level VARs with Granger tests and meta-IRFs. Three main results emerge. First, we find that informed trading has a dual role: it helps build belief consensus in the book (H1a) while simultaneously consuming internal liquidity (depth) (H1b). Second, and most critically, belief consensus is a markedly superior predictor of subsequent volatility than VPIN; Conditional Probability Tables confirm that a high degree of consensus sharply increases the probability of the lowest-volatility state (H2). Third, VAR analysis reveals a unanimous, bidirectional, yet asymmetric loop: belief consensus robustly reduces volatility, while volatility, in turn, erodes consensus (H3). The causal links for VPIN, in contrast, are sporadic and size-dependent. Our results establish a new informational channel, demonstrating that the market's latent belief structure is a more potent and reliable determinant of short-term risk than the realized toxicity of order flow.

1. Introduction

Informed traders are thought to contribute to volatility through their trading activities, which reflect the incorporation of new information into prices. Nevertheless, although the relationship between informed trading and market volatility has been the subject of extensive research, the literature to date has produced mixed results as to the direction of the relationship between the two. Some studies suggest that high levels of informed trading, which lead to an imbalance between informed and uninformed traders (market

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toxicity), can increase liquidity-induced volatility (Easley et al., 2012). However, other research indicates that informed trading tends to reduce volatility by accelerating the integration of firm-specific information into prices (Easley et al., 1998; Hu, 2018; Avramov et al., 2006) in heavily traded and highly capitalized stocks (Blasco and Corredor, 2017).

Unravelling these interrelationships is particularly important, given that volatility is known to have significant adverse effects on market stability. One of the most commonly used measures for quantifying this activity is the Volume-Synchronized Probability of Informed Trading (VPIN) (Easley et al., 2011). VPIN serves as a barometer of information asymmetry by measuring order flow imbalance. High VPIN, indicating extreme market toxicity, is linked to exacerbated volatility (Abad et al., 2018). The proposed mechanism is twofold: market toxicity is associated with high adverse selection risk, which can lead to a sudden disappearance of market liquidity and increased volatility (Rzayev and Ibikunle, 2019; Brunnermeier and Pedersen, 2009); high VPIN is also correlated with investor sentiment, which itself impacts volatility (Gao et al., 2022).

This focus on executed trade imbalances (VPIN), however, captures only one side of market dynamics—the impact of realized flow. The other side, the latent structure of the order book, remains under-explored as a primary information channel.

Our central contribution is to shift the focus of short-horizon volatility analysis from executed trade imbalances (VPIN) to the geometry of latent orders (SLOPE). We investigate the hypothesis that the aggregated "belief consensus" embedded in the Limit Order Book (LOB) is a dominant, forward-looking stabilizer of volatility. By demonstrating this, we provide a new informational channel linking market microstructure and risk dynamics.

This shift in focus is warranted. While traditional theories posit that informed traders use market orders to capitalize on urgent information, a robust body of work suggests this is an incomplete narrative. Theoretical expositions (Seppi, 1997; Harris, 1998; Kaniel and Liu, 2006; Goettler et al., 2009) and empirical studies (Bloomfield et al., 2015; Anand et al., 2005) demonstrate that informed traders also strategically employ limit orders, particularly in conditions of high informational volatility (Pascual et al., 2010). This implies that the LOB itself is not merely a passive source of liquidity but an active repository of market expectations and information.

In this context, the slope of the Limit Order Book (SLOPE) offers a comprehensive metric. It captures not just depth but also the real-time shape of market liquidity and belief consensus (Westland, 2021). Our empirical analysis treats SLOPE as this proxy for market consensus. This construct is distinct from simpler digit-based price clustering (Cont et al., 2014; Schwartz et al., 2004; Baig et al., 2023; Lobão et al., 2024) and provides a more holistic approach by encompassing the full price-depth relationship as it constantly adapts to the inflow of new orders and the cancellation of existing ones (Magris et al., 2023; Løkka, 2014). We examine how this SLOPE co-moves with informed trading (VPIN) and volatility, controlling for spreads, trading activity, and firm size.

The objective of this study is threefold: First, it aims to analyze the impact of informed trading on consensus within the LOB (SLOPE) and its effects on external and internal liquidity. Second, the study seeks to shed light on market volatility dynamics by examining the relationship between informed trading, belief consensus, and volatility, utilizing Granger causality tests to identify causal links. Finally, aligning with our core contribution, the third objective is to assess whether the LOB slope can complement or even surpass VPIN in explaining volatility, weighing the predictive power of belief consensus (SLOPE) against executed toxic flow (VPIN).

To test these dynamics, the study employs a high-frequency, tick-by-tick data analysis considering all LOB levels, using a volume-clock perspective. The analysis is performed on all constituent assets of the IBEX 35. This sample is not merely domestic; it is dominated by large Multinational Enterprises (MNEs), making their home-market valuation and stability dynamics—which we analyze—critical for their global cost of capital. These assets are traded on the SIBE platform—a standard, electronic, order-driven Central Limit Order Book (CLOB) architecture representative of major global exchanges. Furthermore, the study period includes the COVID-19 pandemic, a "black swan" event characterized by extreme uncertainty and volatility (Broadstock et al., 2021; Ali et al., 2020; Ramelli and Wagner, 2020; Albulescu, 2021; Ashraf, 2020; Baig et al., 2021; Zaremba et al., 2021). This period provides a natural "stress test," making it an opportune time to study these complex dynamics under pressure.

This study contributes to the market microstructure literature by being the first, to our knowledge, to systematically incorporate the geometry of LOB information (SLOPE) to study its interplay with informed trading (VPIN) and volatility. We argue that the discovery of this new informational channel has a high degree of generalizability. This generalizability rests on two pillars: (1) the multinational nature of our sample (MNEs), whose home-market dynamics are globally relevant, and (2) the structural equivalence of the SIBE platform (a CLOB) to other modern, order-driven markets. By testing this fundamental mechanism (latent consensus vs. realized flow) with a methodologically robust (tick-by-tick) approach in this setting during a period of extreme stress, our findings are broadly applicable.

The remainder of the study is organized as follows. Section 2 presents a review of the relevant literature. Section 3 describes the data employed in the study, while Section 4 details the methodology and presents the results; Section 5 concludes.

2. Literature review

It is necessary to examine the interaction between informational volatility and liquidity-driven volatility in financial markets, particularly due to the complexity of their relationship across various stock categories. Informational volatility stems from changes in the perceived value of assets due to new information. In contrast, liquidity-driven volatility arises when liquidity availability or supply shifts cause price fluctuations (Nguyen et al., 2020). emphasize that liquidity shortages, especially during periods of market stress, can amplify volatility by limiting traders' ability to adjust prices in response to new information smoothly. This interaction between liquidity conditions and volatility is especially relevant when examining informed trading, as both forms of volatility can co-occur, shaping overall market behavior in complex ways (Hameed et al., 2010).

The behavior of informed traders, who integrate private, non-public information into prices, is fundamental in shaping these market dynamics. By influencing the speed and nature of price adjustments, informed traders can profoundly affect the market's stability and overall volatility (Gao et al., 2022). However, this role is inherently dual. While contributing to price stability, liquidity is also consumed by informed traders as they execute their strategies. Informed trading can deplete liquidity by reducing the depth of the LOB and widening the bid-ask spread (Heflin and Shaw, 1998). Nevertheless, despite the liquidity-consuming nature of informed trading, it simultaneously contributes to a more efficient price discovery process by aligning prices more closely with their fundamental values.

One widely used metric to capture informed trading is the Volume-Synchronized Probability of Informed Trading (VPIN). VPIN quantifies the likelihood that trading volumes are driven by informed traders, offering a dynamic measure of order flow imbalance, which can serve as a leading indicator for extreme market events like flash crashes (Easley et al., 2012). This measure is particularly relevant in high-frequency trading (HFT) environments, where the presence of informed traders, relative to uninformed participants, can lead to market toxicity—an imbalance that exacerbates liquidity issues and, in turn, volatility (Rzayev and Ibikunle, 2019). VPIN provides crucial insights into how informed trading can contribute to or mitigate sudden price movements by tracking the degree of order flow imbalance.

The literature's focus on realized flow (VPIN) overlooks the rich information contained within the latent order book. From a microstructural perspective, this is a critical omission, as informed traders are not limited to market orders. Foucault (Foucault et al., 2005) discusses how informed traders are more likely to utilize limit orders as an effective means of liquidity provision, contrary to the common assumption that market orders are preferred due to their immediacy (Foucault et al., 2013a).

Alongside VPIN, another key variable to consider is the slope of the LOB, which reflects the distribution of orders at various price levels. This measure serves as an indicator of consensus among market participants and market liquidity. A steeper slope signals that orders are more concentrated around certain price points, suggesting stronger consensus among traders about the asset's fundamental value. This increased consensus tends to stabilize market prices, resulting in lower volatility. On the other hand, a flatter slope indicates more dispersed orders, reflecting greater uncertainty among traders and, thus, higher volatility (Jain et al., 2016). The slope of the LOB can also be seen as a measure of the market's elasticity in response to price changes. A steeper slope, which also signals higher liquidity, allows for smoother price adjustments as market participants converge on a shared understanding of asset values.

The relationship between liquidity, slope, and volatility becomes even more relevant when considering high-frequency trading environments. In these markets, the interactions between order flow imbalance (captured by VPIN) and the beliefs of market participants (represented by the slope of the LOB) play a critical role in shaping market outcomes. The concentration of informed traders' orders within the LOB contributes to forming a consensus on fundamental asset values, dampening volatility by aligning market prices with these values. Conversely, when there is a broader dispersion of orders, reflected in a flatter slope of the LOB, the market is more susceptible to price swings driven by uncertainty in trader beliefs.

Combining VPIN with the slope of the LOB provides a robust framework for assessing how informed trading impacts market behavior. VPIN offers a way to predict periods of heightened volatility by measuring the imbalance in the order flow. At the same time, the slope of the LOB captures how beliefs about asset values are distributed among market participants. This dual approach allows for a more comprehensive understanding of how informed traders influence market stability. The relationship between informed trading and market dynamics can be further elucidated by examining how the slope of the LOB reflects pre-trade intentions. A steeper slope suggests traders place their limit orders around prices that reflect their sights, thereby aligning market prices more closely with fundamental values. Conversely, a flatter slope indicates greater belief dispersion, suggesting uncertainty among market participants, which often results in higher volatility as traders react to divergent expectations (Cenesizoglu et al., 2014; Kang and Zhang, 2013).

An additional layer of complexity is introduced when considering how these dynamics vary across different capitalization categories. Large-cap stocks, with their deeper liquidity, typically exhibit more stable pricing and are less sensitive to external shocks. By contrast, small-cap stocks, characterized by lower liquidity, are more susceptible to sharper price swings during periods of market turbulence. Studies (Salisu et al., 2017; Jena et al., 2021) have shown that small-cap stocks tend to experience greater volatility when liquidity is fragmented, further underscoring the differential impact of informed trading across the market capitalization spectrum. This contrast highlights the importance of liquidity in modulating the effects of informed trading on market stability, as liquidity constraints can exacerbate volatility in less liquid stocks (Kulshrestha and Bhaduri, 2019).

This comprehensive literature review highlights the intricate relationships between informed trading, liquidity, and volatility. It underscores the importance of both VPIN (as a measure of realized flow) and the slope of the LOB (as a measure of latent consensus) as tools for understanding market dynamics. However, the relative importance and causal interplay between these two forces, particularly the idea that LOB consensus might be a dominant stabilizer over flow toxicity, remains an open question. The insights gained from these variables, especially in high-frequency trading environments, are critical for developing strategies to manage liquidity risks and mitigate volatility during periods of market stress.

Consistent with the literature summarized above, we test the following hypotheses:

- **(H1a)** Informed trading improves the consensus of beliefs of investors in the LOB.
- **(H1b)** Informed trading consumes external and internal liquidity.
- **(H2)** The dispersion of beliefs in the LOB is a better predictor of market volatility than informed trading.
- **(H3)** There is a positive Granger-causal relationship between informed trading and consensus in large- and mid-cap stocks, alongside a bidirectional negative Granger-causal link between consensus and volatility.

3. Data and measures

3.1. Data

Our sample consists of 32 Spanish stocks belonging to the IBEX 35 index, divided into two 11-stock portfolios representing large and mid-cap and 10-stock portfolio for small-cap. Stocks were chosen for each category based on their belonging to IBEX 35 during 2019 and 2020. The time frame spans from 2nd January of 2019–31 st December of 2020, encompassing the COVID-19 crisis, pandemic crash (CRASH) from January 21st, 2020, to March 17th, 2020; short selling ban (SSB) from March 18th, 2020, to May 18th, 2020; de-escalation (DECAL) from May 19th, 2020, to July 13th, 2020.

The high-frequency dataset includes trading volumes, order book data and high-frequency data for each stock at a millisecond level, obtained directly from Bolsas y Mercados Españoles (BME), the company that manages the Spanish stock exchanges. The trading activity occurs through the Spanish Stock Exchange Interconnection System (SIBE), the technical trading platform where the order book is located. Trading is continuous from 9:00 a.m.–5:30 p.m., with regular call auctions at the opening and closing. Auctions are excluded from the sample, meaning only data from 9:00 a.m.–5:30 p.m. are considered. This allows us to focus on the trading activity of the most liquid Spanish stocks during the main trading hours. Following (Easley et al., 2011), the event clock approach is applied. An analysis of each time bucket as a distinct event period is conducted, and the final value from each bucket is identified to calculate all the relevant measures. The metrics used to investigate the interaction between liquidity, informed trading and volatility and test the hypotheses are presented below.

3.2. Level of informed trading: VPIN

The level of informed trading is determined thanks to the VPIN measure of (Easley et al., 2011), which is based on the imbalance between buy and sell orders and accentuates volume information over pricing data.[3] The process followed to obtain this indicator is as follows. First, the bucket size “V” is defined as one-fiftieth of the average 2019 (ex-auctions) daily volume, as in the original measure. Then, trades are processed individually (trade-by-trade) rather than being aggregated into fixed one-minute intervals. For each trade, the volume and price change are recorded directly. Consecutive trades are accumulated until a volume bucket is filled. The final order price in the bucket is used to compute the bucket return. Depending on trading activity, a volume bucket may encompass multiple trades or only a portion of one. In the original method, all shares transacted within a minute are considered to have been executed at the final price of that minute. In our approach, we consider each order and assign the final price to all shares within that order instead of the final price of the minute.

VPIN is characterized as the aggregate of absolute variances between buy and sell volumes in each volume bucket. The trade direction is determined through probabilistic volume categorization using the bulk volume classification approach. Specifically, “Buy volume” is derived by multiplying the trade volume by the cumulative distribution function (CDF) of the standard normal distribution assessed at the standardized price change, Z $\left(\frac{P_i - P_{i-1}}{\sigma_{\Delta P}}\right)$, where $\sigma_{\Delta P}$ represents the estimated weighted standard deviation of price changes between trades. Sell volume is determined as trading volume multiplied by 1-Z $\left(\frac{P_i - P_{i-1}}{\sigma_{\Delta P}}\right)$. If there is no price change from the start to the end of a sequence of trades, the volume in those trades is divided equally between buy and sell volumes. If the price rises (falls), the volume is weighted more towards buys (sells) than sells (buys). In each volume bucket τ, $V_\tau^{B(S)}$ signifies the cumulative buy (sell) volume and is defined as follows:

$$V_\tau^B = \sum_{i=t(\tau-1)+1}^{t(\tau)} V_i \cdot Z\left(\frac{P_i - P_{i-1}}{\sigma_{\Delta P}}\right) \tag{1}$$

$$V_\tau^S = \sum_{i=t(\tau-1)+1}^{t(\tau)} V_i \cdot \left[1 - Z\left(\frac{P_i - P_{i-1}}{\sigma_{\Delta P}}\right)\right] = V - V_\tau^B \tag{2}$$

Where V_i represents the volume of trade i, meaning the number of shares traded in a specific transaction within the interval of a volume bucket and V is the bucket size, defined as one-fiftieth (1/50) of the average daily volume in 2019 (excluding auctions). This determines how much volume must accumulate before a bucket is considered full, and VPIN can be calculated. $t(\tau)$ is the index of the last trade included in the τ volume bucket, which allows for determining the range of trades that belong to bucket τ. By processing each trade individually and assigning the final price of each order to all shares within that order, we aim to capture the immediate impact of each transaction on the order flow imbalance, leading to a more responsive and precise estimation of VPIN. This approach differs from the original methodology, which assigns the final price of the minute to all shares transacted within that minute.

VPIN is defined as in Eq. (3), where the bucket size n encompasses the aggregate number of volume buckets. VPIN is estimated

[3] VPIN is based on what is commonly referred to as the “event clock” or “volume clock”, contrasting with the usual “calendar clock” based on fixed time intervals. “Event-clock” models are based on the occurrence of events, such as individual trades or changes in trading volume and have been proposed to address the complexity of computing correlations in intraday data due to random and asynchronous transactions. The benefits of using event-clock models for analyzing intraday data were highlighted by (Kelly, 2005). These models offer significant statistical advantages, such as eliminating intrasession seasonal effects and restoring some degree of normality to the data (Clark, 1973; Ling, 2017).

utilizing a moving window of L-length volume buckets. For example, the initial VPIN calculation employs volume buckets within the interval (Easley et al., 2012; DerSimonian and Laird, 1986). Successive VPIN estimations are derived by incrementally shifting the moving window, for instance, from the range (Easley et al., 1998; Glosten and Milgrom, 1985) in the 50-length case, and proceeding accordingly.

$$VPIN = \frac{\left(\sum_{\tau=1}^{n} \left|V_\tau^S - V_\tau^B\right|\right)}{n \cdot V} \tag{3}$$

Then, the empirical CDF of VPIN is used to convert each VPIN reading into a cumulative probability. The empirical CDF is calculated over the rolling window of 50 VPIN values, providing a probabilistic interpretation of the current VPIN relative to its recent history. This approach helps identify periods when the VPIN reaches extreme values, indicating potential surges in informed trading activity. A high CDF value may indicate a period of high activity by informed traders, whereas a low value may suggest the opposite.

To ensure that our metrics can be applied across markets, all variables are normalized stock-by-stock and expressed in percentile space through empirical cumulative distribution functions (CDFs). This normalization allows VPIN and SLOPE to be interpreted on a common 0–1 scale, making their marginal effects comparable across venues that differ in tick size, trading intensity, or depth. The event-time (volume-clock) framework further abstracts from local trading hours or time-zone effects, allowing replication in any electronic order-driven market. Following the same protocol researchers can reproduce our design in other markets using standard LOB data. These methodological choices are therefore aimed at portability and comparability rather than at tailoring to Spanish market idiosyncrasies.

3.3. Liquidity and dispersion of beliefs measures

Relative quoted spread (RS) and depth of the LOB are used as indicators that provide insights into different aspects of liquidity: We use RS (as shown in Eq. 4) as a proxy for external liquidity, representing the difference between bid and ask prices, which reflects the costs associated with market impact. In contrast, we refer to the internal liquidity of the LOB through the depth of the LOB (outlined in Eq. 5).

$$RS_{i,\tau} = \quad 2x(Best\ ask\ price_i \quad - Best\ bid\ price_i)_i / (Best\ ask\ price_i + Best\ bid\ price_i) \tag{4}$$

$$DEPTH_{i,\tau} = (Avg\ ask\ orders + Avg\ bid\ orders)/2 \tag{5}$$

$DEPTH_{i,\tau}$ refers to the average accumulated shares in all positions different from zero for both the best bid and the best ask positions. A greater depth means that any transaction will have less impact on prices. Therefore, increased depth indicates higher liquidity in the LOB and a greater ability to absorb the effects of large trades. In this study, RS, depth, and slope of the LOB are not calculated in daily intervals but instead in intraday volume intervals (or buckets), with the last value of each bucket being used for analysis.

The slope of the LOB reflects the dispersion of beliefs within the limit order book. A steeper slope indicates a tighter concentration of displayed depth around prevailing prices—i.e., stronger belief alignment—a construct distinct from digit-based price clustering. Conversely, a flatter slope suggests greater belief dispersion and less accuracy in the underlying information driving prices. In this study, we treat SLOPE as a book-shape proxy for liquidity density and consensus. Its strength as a metric lies in its comprehensive nature: it moves beyond top-of-book quotes to capture the entire LOB structure, integrating both the spread and the depth across all buy and sell orders (Kempf and Mayston, 2008).

While SLOPE acts as a measure of consensus, it also inherently captures liquidity dynamics. Although we do not assume a steep slope is informed, a body of literature suggests that informed traders actively “create” it. In contexts of high informational asymmetry, a steeper slope can reflect the activity of informed traders shaping the order book and accelerating the price discovery process (Nguyen et al., 2020). This link between the LOB’s shape and its informational content is reinforced by studies demonstrating that the LOB state effectively predicts short-term price changes (Cenesizoglu et al., 2014). Furthermore, (Maglaras et al., 2015) notes that a greater order flow imbalance—often associated with concentrated informed trading—tends to result in a steeper slope.

The slope of the demand side and the supply side in the visible order book is obtained following (Næs and Skjeltorp, 2006) as in Eqs. (6), (7) and (8).

$$SE_{i,\tau}^S = \frac{1}{N_A}\left\{\frac{v_1^A}{p_1^A/p_0^A - 1} + \sum_{l=1}^{N_B}\frac{v_{l+1}^A/v_l^A - 1}{p_{l+1}^A/p_l^A - 1}\right\} \tag{6}$$

$$DE_{i,\tau}^S = \frac{1}{N_B}\left\{\frac{v_1^B}{\left|p_1^B/p_0^B - 1\right|} + \sum_{l=1}^{N_B}\frac{v_{l+1}^B/v_l^B - 1}{\left|p_{l+1}^B/p_l^B - 1\right|}\right\} \tag{7}$$

$$SLOPE_{i,\tau} = \frac{1}{N_i}\sum_{s=1}^{N_i}\left\{\frac{SE_{i,\tau}^S + DE_{i,\tau}^S}{2}\right\} \tag{8}$$

Where $SE_{i,\tau}^S\left(DE_{i,\tau}^S\right)$ are the average slope estimates of the supply (demand) side for security i during bucket τ, and measure the average rate at which available volume changes relative to price changes on the ask and bid sides. The parameter N_A (N_B) represents the total number of ask (bid) price or tick level l, containing orders in the LOB. The price level index l= 0 denotes the bid-ask midpoint, calculated as $p_0 = \frac{p_0^A + p_0^B}{2}$, where p_0^A (p_0^B) is the best ask (bid) price. The level l= 1 corresponds to the best available quote with volume on each market side. The variable v_l is defined as the natural logarithm of the accumulated total share volume at each price level l. This logarithmic transformation normalizes the volume data, facilitating a more consistent comparison across different price levels and securities. $SLOPE_{i,\tau}$ is the last observed slope for security i at the end of each bucket τ. This metric provides a summarized assessment of the LOB's liquidity and depth during each specific period, besides serving as a measure of belief consensus.

The volatility of intraday returns is proxied throughout this study primarily using conditional volatility estimated through an EGARCH (1,1) model (Eq. 9). This approach is well-suited for capturing volatility's persistence, clustering, and asymmetric response to shocks. Unlike traditional GARCH models, EGARCH directly models the logarithm of conditional variance, which allows to capture leverage effects—where negative news increases volatility more than positive news of the same magnitude.

We adopt EGARCH (1,1) as our baseline measure due to its parsimony and comparability across stocks in event-time. Model selection was based on information criteria (AIC/BIC), and model adequacy was confirmed by residual diagnostics. Preliminary diagnostics support the use of GARCH-type models: Augmented Dickey–Fuller (ADF) tests reject the unit root hypothesis ($p < 0.001$) for all return series, and pre-estimation ARCH–LM tests are highly significant ($p < 0.001$). After estimation, 8 out of 32 stocks (~25 %) show no detectable residual heteroskedasticity (post-estimation ARCH–LM $p > 0.05$), while the remainder still exhibit some, indicating incomplete but non-zero filtering. In all cases, the EGARCH(1,1) specification significantly reduces autocorrelation in squared residuals compared to non-parametric measures (e.g., within-bucket standard deviation), which fail to remove second-order dependence and are more sensitive to outliers. We therefore retain EGARCH(1,1) as the homogeneous volatility series across assets. We report specification checks (GJR/APARCH; skew-t and GED innovations). For H2, we re-estimate the predictive tables using an alternative proxy based on absolute return residuals (Eq. 11), obtaining qualitatively similar patterns. H1 and the VAR/Granger exercises (H3) rely on the main EGARCH series.

The equation for an EGARCH (1, 1) model is expressed as follows, with ς_t representing the conditional volatility.

$$\log\left(\sigma_t^2\right) = \omega + \sum\nolimits_{i=1}^{p} \alpha_i g(Z_{t-i}) + \sum\nolimits_{j=1}^{q} \beta_j \log\left(\sigma_{t-j}^2\right); \varsigma_t = \exp\left(\frac{\log\left(\sigma_t^2\right)}{2}\right) \tag{9}$$

Where $\log\left(\sigma_t^2\right)$ is the natural logarithm of the conditional variance in period t. The function $g(Z_{t-i})$, defined as $g(Z_{t-i}) = \theta Z_{t-i} + \gamma(|Z_{t-i}| - E[|Z_{t-i}|])$, captures the effects of past shocks (Z_{t-i}) in volatility, where θ and γ allow the model to incorporate asymmetries and leverage effects. ς_t is conditional volatility. Table 1 shows the descriptive statistics for the variables under examination.

For robustness in H2, we replicate the conditional-probability analysis using an alternative volatility proxy based on (Jones et al., 1994) (Eqs. 10–11).

$$R_{i\tau} = \sum\nolimits_{r=1}^{S} b_{i,r} \cdot R_{i,\tau-r} + u_{i,\tau} \tag{10}$$

$$|u_{i\tau}| = \phi_i + \sum\nolimits_{k=1}^{q} \rho_{ik} \cdot |u_{i,\tau-r}| + c_i \cdot bucket + \sum\nolimits_{j=1}^{2} \Psi_i \cdot h_i + \zeta_{i\tau} \tag{11}$$

Where $R_{i\tau}$ is the return of stock i in bucket τ, $u_{i,\tau}$ is the residual, and lags are included to handle autocorrelation. The event clock is proxied by the bucket number, and dummies for hours 9 and 17 account for the U-shape in intraday volatility, following (Jones et al., 1994). The H2 patterns remain qualitatively unchanged under this proxy.

4. Methodology and results

4.1. The non-contemporaneous interplay among informed trading, liquidity, dispersion of beliefs and volatility

We first address hypothesis (H1a) and hypothesis (H1b), investigating the non-contemporaneous impact of informed trading over consensus and liquidity measures. As in (Hendershott and Moulton, 2011) and (Yildiz et al., 2020), we control for trading activity using the average trade size (SIZE) in each bucket as a proxy for the number of trades per bucket. A higher number of trades could indicate greater liquidity and lower transaction costs due to increased competition among market participants. We also control for volatility, a critical factor in assessing market liquidity, as more volatile markets tend to have higher transaction costs due to increased perceived risk. Controlling for volatility is particularly relevant during periods of market stress, where informed traders may withdraw liquidity, leading to increased volatility (Bjursell et al., 2017). Additionally, we control for period windows using dummy variables.

Where the dynamics of market quality are concerned, the multifaceted interplay among liquidity, toxicity, and volatility is encapsulated in our proposed model as in (Yildiz et al., 2020):

$$\begin{aligned} \boldsymbol{Y}_{i,\tau} &= \boldsymbol{\beta}_{i,\tau} + \boldsymbol{\beta}_{i,1} \cdot \boldsymbol{VPIN}_{i,\tau-1} + \boldsymbol{\beta}_{i,2} \cdot \boldsymbol{CRASH}_{i,\tau-1} + \boldsymbol{\beta}_{i,3} \cdot \boldsymbol{SSB}_{i,\tau-1} + \\ &+ \quad \boldsymbol{\beta}_{i,4} \cdot \boldsymbol{DECAL}_{i,\tau-1} + \boldsymbol{\beta}_{i,5} \cdot \boldsymbol{SIZE}_{i,\tau-1} + \boldsymbol{\beta}_{i,6} \cdot \boldsymbol{VOLATILITY}_{i,\tau-1} + \boldsymbol{\varepsilon}_{i,\tau} \end{aligned} \tag{12}$$

The slope of the LOB, market or external liquidity (RS) and internal liquidity of the LOB (DEPTH) are taken as dependent variables $(\mathrm{Y}_{i,\tau})$. $\mathrm{VPIN}_{i,\tau-1}$ proxies for the level of informed trading as measured by VPIN. The dummy variables $\mathrm{CRASH}_{i,\tau-1}$, $\mathrm{SSB}_{i,\tau-1}$, and

Table 1
Descriptive statistics.

	VPIN	CDFVPIN	SLOPE	RS	DEPTH	ABSRES	EGARCH	SIZE	BUCKET
Panel A: Large cap									
Mean	0.0712	0.5017	2070.2351	0.0005	83.6308	0.0013	0.0026	1151.1154	47.1140
Median	0.0611	0.5022	1803.9240	0.0004	82.0000	0.0009	0.0024	156.2869	27.0000
Maximum	0.2079	1.0000	12888.6925	0.0554	954.0000	0.1470	0.0448	833963	775.0000
Minimum	0.0001	0.0000	17.4816	0.0001	21.5000	0.0000	0.0002	0.3308	1.0000
Std. Dev.	0.0312	0.2881	1331.9689	0.0005	31.1035	0.0016	0.0014	12192.5633	61.8409
Skewness	1.0243	-0.0046	2.0533	15.2624	2.6187	13.2224	2.4001	46.0268	3.9823
Kurtosis	3.1685	1.8022	8.9405	819.5322	33.9947	681.6695	19.1456	2780.5268	27.5841
Obs.	261477	261477	261477	261477	261477	261477	261477	261477	261477
Panel B: Mid cap									
Mean	0.0967	0.4997	1513.5797	0.0008	66.8811	0.0013	0.0026	2036.6584	112.2574
Median	0.0939	0.4986	1335.4096	0.0006	66.5000	0.0010	0.0024	112.1728	43.0000
Maximum	0.2374	1.0000	9585.6870	0.0775	337.5000	0.0961	0.0185	332965	2228.0000
Minimum	0.0048	0.0000	22.0008	0.0001	20.0000	0.0000	0.0005	1.1476	1.0000
Std. Dev.	0.0235	0.2877	945.1884	0.0009	22.4970	0.0014	0.0009	13707.5277	192.0420
Skewness	0.6196	0.0076	1.6749	8.9661	0.9743	6.9048	2.2088	19.0524	4.0765
Kurtosis	3.3950	1.8012	7.8496	300.5070	8.0025	160.3056	13.5209	430.6169	25.9586
Obs.	376565	376565	376565	376565	376565	376565	376565	376565	376565
Panel C: Small cap									
Mean	0.1144	0.5004	1188.1892	0.0010	61.7774	0.0014	0.0028	551.4249	58.9063
Median	0.1154	0.5004	954.7441	0.0008	63.0000	0.0011	0.0025	47.4682	36.0000
Maximum	0.2296	1.0000	9585.6870	0.0450	169.000	0.0987	0.0212	6881	1222.0000
Minimum	0.0149	0.0000	16.3801	0.0001	20.0000	0.0000	0.0007	0.1381	1.0000
Std. Dev.	0.0258	0.2879	922.9761	0.0011	18.4984	0.0017	0.0012	3066.6210	77.1205
Skewness	-0.1793	-0.0002	2.6186	7.8197	0.0523	7.9366	2.2794	11.2973	4.7725
Kurtosis	3.4172	1.8020	12.8104	145.3807	2.6100	208.1462	11.9347	149.1891	44.9396
Obs.	280215	280215	280215	280215	280215	280215	280215	280215	280215

Table 1 presents the descriptive statistics of the selected variables, distinguishing between large-, mid- and small-cap portfolios. All statistics refer to the 2nd of January 2019–31 st of December 2020 period.

$DECAL_{i,\tau-1}$ reflect the COVID-19 crash window (CRASH), the regulatory imposition of a short-selling ban (SSB) and de-escalation (DECAL). These dummies take a value of 1 when the respective events occur, and zero otherwise. $SIZE_{i,\tau-1}$ explains average traded size of the bucket, while $Volatility_{i,\tau-1}$, is conditional volatility measured by an EGARCH (1,1) process.[4] Each coefficient $\beta_{i,1}$, $\beta_{i,2}$, $\beta_{i,3}$, $\beta_{i,4}$, $\beta_{i,5}$ and $\beta_{i,6}$ is instrumental in gauging the impact of these market quality measures on liquidity (or belief consensus) in the subsequent period τ. The error term $\varepsilon_{i,\tau}$ accommodates for unobserved factors and stochastic variations affecting liquidity. We refer to each stock with sub-index *i*. The variables are treated to solve inherent problems such as heteroscedasticity. In all stock-level regressions, we systematically include a consistent set of lagged controls at τ–1—CRASH, SSB, DECAL, SIZE, and conditional volatility (VOLATILITY)—to mitigate confounding biases and isolate lead–lag relations.[5]

We present the results concerning the non-contemporaneous relationship between informed trading (measured by VPIN), market consensus in the Limit Order Book (SLOPE), and liquidity metrics (relative spread as external liquidity, and depth as internal liquidity) across three asset categories: large-cap, mid-cap, and small-cap stocks. We structure our analysis to explicitly test our two primary hypotheses: (H1a) Conditional on controls, increases in informed trading are, on average, associated with higher belief consensus in the LOB (SLOPE), with heterogeneity across stocks and by market-cap segment; and (H1b) Informed trading consistently reduces internal liquidity (DEPTH) while its impact on external liquidity (RS) is weak or ambiguous. Due to substantial cross-sectional heterogeneity detected in preliminary diagnostics, we use a random-effects meta-analytic approach (DerSimonian and Laird, 1986) as our primary method. We subsequently reinforce these findings using panel data regressions with Driscoll-Kraay robust standard errors as a robustness check.

To rigorously account for this heterogeneity, we first estimate individual OLS regressions for each stock separately within each capitalization category, obtaining individual coefficients and robust standard errors. Subsequently, we aggregate these estimates via random-effects meta-analysis, assigning greater weight to more precise estimates (i.e., inverse-variance weighted mean). This methodological choice was validated by significant heterogeneity tests (Cochran's Q and I^2 statistics), confirming the presence of substantial variability across individual securities. The results of these analyses, including group-level meta-analytic estimates and

[4] A robustness test was performed using absolute value of the return (Equation 11).

[5] These controls are motivated by prior microstructure evidence showing that market-wide shocks, trade size, and volatility are joint determinants of informed trading and limit order book conditions. Empirically, their omission produces material changes in the estimated coefficients of the main explanatory variables for a non-trivial subset of stocks. The sensitivity analysis (summarized in Figures A1 and A2, Appendix A) shows that removing individual controls can alter the SLOPE → volatility coefficient by more than 200 % and the VPIN → SLOPE coefficient by over 3000 % in some cases. Including this control set in all specifications thus ensures that the estimated lagged effects are conditional associations, not spurious correlations driven by these confounders. This approach is further corroborated by our fixed-effects panel estimations (Driscoll–Kraay) and VAR/Granger tests.

individual-level summaries, are reported separately for each capitalization group.

For large-cap stocks, Table 2 (Panels A–C) presents the meta-analytic coefficients, the share of significant stocks, and the individual stock-level estimates. Consistent with Hypothesis (H1a), we find that informed trading positively and significantly impacts investor consensus in the limit order book This is indicated by the positive and statistically significant meta-analytic coefficient for lagged VPIN (1.4871, $p = 0.0213$). This finding suggests that increased informed trading aligns market beliefs, potentially as uninformed or liquidity-driven traders reduce their activity, causing the remaining orders to reflect more homogeneous informed views (Glosten and Milgrom, 1985).

Regarding Hypothesis (H1b), which states that informed trading consumes liquidity, we find partial support. The impact on internal liquidity (DEPTH) is unambiguous: we find a strong, negative, and statistically significant relationship (–0.8352, $p = 0.0032$),

Table 2
Non-contemporaneous relationship between consensus, liquidity, and informed trading in Large Cap.

PANEL A Meta-analytic coefficient for 11 individual regressions of large-cap stocks

LARGE CAP	$VPIN_{\tau-1}$	$CRASH_{\tau-1}$	$SSB_{\tau-1}$	$DECAL_{\tau-1}$	$SIZE_{\tau-1}$	$VOLATILITY_{\tau-1}$
SLOPE	1.4871**	-0.1822***	-0.4794***	-0.4990***	-0.0001***	-250.4969***
	(0.6458)	(0.0494)	(0.1257)	(0.1111)	(0.0000)	(20.6474)
RS	-0.2878	-0.0172	0.1267*	0.0069	0.0001***	138.2882***
	(0.2209)	(0.0195)	(0.0525)	(0.0218)	(0.0000)	(9.9650)
DEPTH	-0.8352***	0.0231	-0.0952**	0.0962**	-0.0000***	-107.0391***
	(0.2834)	(0.0138)	(0.0374)	(0.0450)	(0.0000)	(13.6848)

PANEL B Percentage of large-cap stocks with significant effects (lagged VPIN)

LARGE CAP	*% Positive Significant*	*% Positive Non-significant*	*% Negative Significant*	*% Negative Non-significant*	*N stocks*
SLOPE	54.5 %	18.2 %	9.1 %	18.2 %	11
RS	27.3 %	9.1 %	54.5 %	9.1 %	11
DEPTH	9.1 %	9.1 %	63.6 %	18.2 %	11

PANEL C Individual regressions of large-cap stocks

SLOPE 10^{-3} *RS* 10^{3} *DEPTH* 10^{-2}		*C*	$VPIN_{\tau-1}$	$CRASH_{\tau-1}$	$SSB_{\tau-1}$	$DECAL_{\tau-1}$	$SIZE_{\tau-1}$	$VOLATILITY_{\tau-1}$	*ADJ* R^2
LARGE CAP	ITX	2.4421***	-2.4163***	0.0591***	-0.1104***	-0.1268***	-0.0002***	-172.8776***	0.3135
		0.0512**	1.8867***	-0.0868***	-0.0063	-0.0376***	0.0001***	111.2879***	0.2739
		1.4831***	-0.6811**	-0.0683***	-0.0511***	0.1232***	-0.0001***	-117.7880 ***	0.4034
	IBE	3.6893***	3.2559***	-0.6398***	-0.1717***	-0.9995***	-0.0001***	-347.6680***	0.3795
		0.1624***	-0.5771***	0.0720***	-0.0213**	0.1016***	0.0000***	96.1383***	0.2729
		1.3391***	-0.4819**	0.1294***	-0.0671***	0.3893***	-0.0000***	-188.9465***	0.4642
	SAN	5.3069***	8.5619***	-0.5674***	-1.4976 ***	-0.8779***	-0.0001***	419.2862***	0.1729
		-0.1107***	-0.2942	0.0339***	0.2573***	0.0201***	0.0000***	129.5919***	0.2633
		1.0136***	-1.4313***	0.1209***	-0.0173*	0.1012***	-0.0000***	-74.6745***	0.0851
	BBVA	4.7780***	-0.2315	-0.2563***	-1.6410***	-1.5813***	-0.0001***	-308.4001***	0.3377
		-0.0753***	0.7716***	0.0113	0.2741***	0.0935***	0.0000***	122.3548***	0.3214
		1.0040***	-0.7585***	0.0090**	0.2002***	0.3621***	-0.0000***	-98.2735***	0.3624
	CABK	2.6415***	0.0254	0.0342***	-0.0039	0.0280**	-0.0000***	-247.7006***	0.0910
		0.2366***	-1.4428***	-0.0469***	0.1216***	-0.0766***	0.0000***	156.4919***	0.1735
		1.2175***	0.3802***	0.0431***	-0.1585***	-0.0976***	-0.0000***	-106.7579***	0.3175
	AMS	2.2280***	-0.6633	-0267*	0.0849***	-0.0245**	-0.0005***	-158.6826***	0.0945
		-0.0211	0.7747**	-0.0304***	0.0002	-0.0558***	0.0004***	128.5082***	0.2053
		0.9679***	-0.0657	0.0116***	-0.1830***	0.0093***	-0.0002***	-63.2827***	0.4419
	TEF	4.8975***	2.3779*	-0.6242***	-1.4347***	-1.6315***	-0.0001***	-314.4587***	0.3532
		-0.0362**	-0.5799**	0.0063	0.1104***	0.0545***	0.0000***	137.9338***	0.3134
		1.0346***	-0.1055	0.0187***	-0.0267***	0.2342***	-0.0000***	-100.3121***	0.3431
	NTGY	1.8274***	0.7311***	-0.0944***	-0.3869***	-0.0540***	-0.0000***	-267.5910***	0.1565
		0.3102***	-0.5006***	0.0747***	0.4137***	-0.0186***	0.0000***	195.5225***	0.2509
		1.0663***	-0.7802***	-0.0173***	-0.2631***	0.0265***	-0.0000***	-155.9586***	0.4894
	AENA	1.2302***	4.6809***	0.1394***	0.0453***	-0.2763***	-0.0009***	-184.7428***	0.3707
		0.2759***	-1.9092***	-0.1234***	0.1002***	0.1388***	0.0011***	181.7418***	0.4026
		1.0573***	-2.3625***	-0.0404***	-0.1147***	0.1138 ***	-0.0006***	-37.5937***	0.3241
	FER	1.7748***	1.3583***	0.0245*	-0.2507***	-0.1762***	-0.0003***	-108.4567***	0.2188
		0.2621***	0.0381	-0.0885***	0.1372***	-0.0639***	0.0002***	106.3821***	0.2719
		0.9853***	0.1841	-0.0049	-0.1289***	0.0262***	-0.0002***	-73.3572***	0.4544
	REP	2.5886***	1.6370***	-0.1243***	0.0629**	0.1078***	-0.0001***	-240.9494***	0.0997
		0.1312***	-0.8253***	-0.0149**	0.0062	-0.0801***	0.0001***	155.2201***	0.2078
		1.7658***	-3.0890***	0.0544***	-0.2359***	-0.2296***	-0.0000***	-160.8817***	0.5251

Table 2. Panels A–C report, respectively, random-effects meta-analytic coefficients (inverse-variance weighting across stock-level OLS), the share of large-cap stocks with significant positive/negative coefficients for lagged *VPIN*, and individual stock regressions with heteroskedasticity-consistent (MacKinnon–White) standard errors. All variables are winsorized at the 1st/99th percentiles within stock. All specifications include lagged controls (*CRASH*, *SSB*, *DECAL*, *SIZE*, *VOLATILITY*). *, **, and *** denote statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

confirming that informed trading erodes book depth. In contrast, the impact on external liquidity (RS) is statistically insignificant (–0.2878, $p = 0.1927$). While the negative sign would suggest enhanced liquidity, the high p-value prevents any strong conclusions. This lack of significance suggests the impact is either weak or, as indicated by Panel B, reflects substantial heterogeneity across individual stocks.

Moreover, the control variables perform as expected. Periods of market instability (CRASH) and regulatory restrictions on short-selling (SSB) are associated with a significant reduction in investor consensus (–0.1822 and –0.4794, respectively, $p < 0.001$) and also negatively affect internal liquidity. These results underscore that market-wide shocks and regulatory interventions significantly disrupt liquidity provision and belief formation processes. The remaining control, average trade size (SIZE) and conditional volatility (VOLATILITY), also display significant impacts, supporting the established literature indicating that larger trade sizes and higher volatility negatively affect liquidity provision (Hasbrouck and Seppi, 2001; Chordia et al., 2000).

For mid-cap stocks (Table 3, Panels A–C), the results show a clear distinction from the large-cap group. In line with Hypothesis (H1a), the meta-analytic coefficient for VPIN on SLOPE is positive (1.4820) but only marginally significant ($p = 0.0691$). While this average magnitude is similar to large caps, the consistency of the effect, shown in Panel B, is markedly stronger: 72.7 % of mid-cap stocks exhibit a significant positive relationship, compared to only 54.5 % for large caps. This reinforces H1a, suggesting the consensus-building effect of informed trading is more widespread and reliable in this segment.

Regarding liquidity consumption (H1b), the findings parallel the large-cap results. Informed trading exhibits a significant negative impact on internal liquidity (DEPTH), (–0.5392, $p = 0.0180$), confirming that VPIN decreases book depth, likely due to liquidity providers adjusting their positions or reducing quote aggressiveness in response to adverse selection risk. In contrast, the effect of informed trading on external liquidity (RS) is negative but not statistically significant (–0.5855, $p = 0.1835$). This ambiguity, as with large caps, prevents strong conclusions about VPIN's impact on spreads. Additionally, the short-selling ban (SSB) and de-escalation (DECAL) periods, along with conditional volatility, significantly decrease consensus and internal liquidity, confirming their disruptive role.

The analysis of small-cap stocks (Table 4, Panels A–C) reveals the most acute trade-offs. Consistent with Hypothesis (H1a), informed trading positively impacts investor consensus (SLOPE), and does so with the highest statistical confidence of any group (0.6208, $p < 0.001$). This finding suggests the consensus-enhancing effect of informed trading is highly reliable in this segment, presumably as less-informed participants withdraw.

Regarding Hypothesis (H1b), the results confirm a strong negative relationship with internal liquidity (DEPTH). The meta-analytic coefficient (–1.1891, $p < 0.001$) is the largest in magnitude across all size categories, indicating that small-cap stocks are the most sensitive to the adverse selection risk posed by VPIN. Conversely, the effect on external liquidity (RS) is positive but statistically insignificant (0.3079, $p = 0.4238$). These findings imply that informed trading predominantly impacts internal liquidity by discouraging liquidity provision, consistent with theoretical adverse selection costs (Kyle, 1985; Foucault et al., 2013b).

Furthermore, the small-cap group shows the strongest adverse reaction to regulatory intervention. The short-selling ban (SSB) is associated with a significant reduction in consensus (–0.2946, $p < 0.001$), a worsening of internal liquidity (–0.2140, $p < 0.001$), and a significant increase in external liquidity costs (RS: 0.6945, $p < 0.001$). The remaining controls (SIZE, VOLATILITY) align with established literature.

Importantly, these patterns are robust to the alternative volatility specification based on the residuals (Jones et al., 1994): repeating the meta-analytic tests using absolute return residuals as a volatility proxy delivers qualitatively identical results, confirming that the main findings do not depend on the choice of volatility measure.

Taken collectively, these findings underscore the nuanced, dual role of informed trading. In line with Hypothesis (H1a), informed trading consistently enhances investor consensus (SLOPE) across all size groups. However, supporting Hypothesis (H1b), this benefit comes at a cost that is clearly moderated by firm size: the adverse impact of VPIN on internal liquidity (DEPTH), while significant for all segments, becomes most pronounced for small-cap stocks.

Thus, our comparative analysis reinforces that the impact of informed trading on market quality metrics is significantly moderated by firm-specific conditions. This nuanced understanding has important implications for market participants and regulators alike. Finally, these results hold after accounting for our control variables, which confirm that market-wide shocks (CRASH, SSB) consistently and negatively affected consensus and internal liquidity across all size groups, emphasizing the disruptive influence of market instability and trading restrictions.

To ensure the robustness and reliability of our primary meta-analytic results, we conduct additional fixed-effects panel regressions for each market-capitalization group using Driscoll-Kraay standard errors. This panel approach explicitly controls for unobserved time-invariant characteristics of each stock and addresses serial correlation, heteroscedasticity, and cross-sectional dependence (Driscoll and Kraay, 1998; Hoechle, 2007). The Hausman specification test confirmed the suitability of fixed effects, and bandwidth selection for the Driscoll-Kraay estimator followed the Newey-West automatic selection rule (Andrews, 1991).

Table 5 summarizes these fixed-effects panel regression results, which largely corroborate our primary meta-analytic findings. Regarding Hypothesis (H1a) (SLOPE), the panel confirms the positive, significant impact of VPIN for Large Caps (1.8758, $p < 0.01$) and Small Caps (0.7093, $p < 0.05$). Notably, the effect for Mid Caps loses its marginal significance and becomes statistically insignificant (-1.1668, p = n.s.), suggesting this specific finding was sensitive to the estimation method.

With regard to Hypothesis H1b (Liquidity), the panel offers strong confirmation. The negative impact on internal liquidity (DEPTH) is strongly significant ($p < 0.001$) across all three tiers. Furthermore, the effect on external liquidity (RS) remains statistically insignificant in all cases.

Moreover, the control variables —such as market shocks (CRASH, SSB), average trade size (SIZE), and conditional volatility (VOLATILITY)—display consistent patterns across both meta-analytic and panel methodologies. This reaffirms the robustness of our

Table 3
Non-contemporaneous relationship between consensus, liquidity, and informed trading in Mid Cap.

PANEL A Meta-analytic coefficient for 11 individual regressions of mid-cap stocks

MID CAP	$VPIN_{\tau-1}$	$CRASH_{\tau-1}$	$SSB_{\tau-1}$	$DECAL_{\tau-1}$	$SIZE_{\tau-1}$	$VOLATILITY_{\tau-1}$
SLOPE	1.4820*	0.0135	-0.3254***	-0.2056***	-0.0000***	-225.7963***
	(0.8153)	(0.0558)	(0.0605)	(0.0584)	(0.0000)	(17.7095)
RS	-0.5855	-0.0025	0.4042***	0.0585**	0.0001***	211.2325***
	(0.4402)	(0.0362)	(0.0671)	(0.0297)	(0.0000)	(25.5023)
DEPTH	-0.5392**	-0.0194	-0.1426***	0.0293	-0.0000***	-81.4868***
	(0.2279)	(0.0158)	(0.0262)	(0.0249)	(0.0000)	(10.9671)

PANEL B Percentage of mid-cap stocks with significant effects (lagged VPIN)

MID CAP	*% Positive Significant*	*% Positive Non-significant*	*% Negative Significant*	*% Negative Non-significant*	*N stocks*
SLOPE	72.7 %	0.0 %	18.2 %	9.1 %	11
RS	27.3 %	9.1 %	36.4 %	27.3 %	11
DEPTH	18.2 %	18.2 %	54.4 %	9.1 %	11

PANEL C Individual regressions of mid-cap stocks

SLOPE 10^{-3} *RS* 10^{3} *DEPTH* 10^{-2}		C	$VPIN_{\tau-1}$	$CRASH_{\tau-1}$	$SSB_{\tau-1}$	$DECAL_{\tau-1}$	$SIZE_{\tau-1}$	$VOLATILITY_{\tau-1}$	$ADJ\ R^2$
MID CAP	ELE	1.8302***	-0.6677**	0.0686***	0.0482*	-0.0764***	-0.0001***	-152.6652***	0.1245
		0.2696***	-0.0664	-0.0529***	-0.0063	0.0375*	0.0001***	133.9652***	0.1922
		1.0628***	-0.6915**	-0.0338***	-0.2073***	0.0101 ***	-0.0001***	-109.4384 ***	0.5584
	MTS	2.5050***	1.4020***	-0.1587***	-0.6587***	-0.3256***	0.0000	-255.5122***	0.0776
		-0.1622***	0.1152	0.1633***	0.6515**	0.0286***	0.0001***	300.8711***	0.2624
		0.5349***	0.2366**	-0.0497***	-0.1495***	-0.0534***	-0.0000***	-28.0907***	0.2766
	CLNX	2.0074***	-0.0995	0.3663***	0.0658***	0.0763***	-0.0007***	-189.7712***	0.0847
		0.0511**	1.2176***	-0.0965***	0.1460***	-0.0680***	0.0007***	135.5943***	0.1555
		1.2091***	-3.3570***	-0.0761***	-0.1416***	0.0519***	-0.0003***	-73.9353***	0.4285
	ACS	2.1135***	1.3301***	-0.1446***	-0.4367***	-0.3432***	-0.0001***	-268.1408***	0.2624
		-0.1761***	0.9614***	0.0910***	0.5471***	0.0967***	0.0001***	246.3666***	0.3097
		0.9751***	-0.6385***	0.0674***	-0.1603***	0.1140***	-0.0001***	-73.6541***	0.3957
	IAG	2.2714***	-2.4956***	0.2910***	-0.3181***	-0.1648***	-0.0000***	-260.1816***	0.1109
		0.0571***	0.3255***	-0.3607***	0.4323***	0.0719***	0.0000***	354.1277***	0.2244
		0.9870***	-0.0485*	-0.0093***	0.0549***	0.0719***	-0.0000***	-121.4755***	0.2252
	GRF	1.5423***	3.6919***	0.1297***	-0.0614***	-0.0184**	-0.0001***	-199.9447***	0.1784
		0.2394***	-0.6388**	-0.0542***	0.2925***	-0.0174**	0.0002***	162.7080***	0.2627
		0.8645***	-0.9712***	-0.0341***	-0.1230***	0.0767***	-0.0000***	-57.0735***	0.3445
	MAP	1.9056***	1.3293***	-0.1891***	-0.4810***	-0.4488***	-0.0000***	-165.2859***	0.2912
		0.3343**	-1.3257***	0.0875***	0.5598***	0.1370***	0.0000***	209.3639***	0.2754
		0.9858***	-0.3318***	0.0479***	-0.0405***	0.1049***	-0.0000***	-105.1172***	0.3717
	BKT	2.3510***	0.7040***	-0.0126	-0.3132***	0.1477***	-0.0000***	-293.3087***	0.1163
		0.1044***	-0.3856*	0.0702***	0.5925***	-0.0153***	0.0000***	200.8212***	0.2652
		0.8419***	0.0494	-0.0436***	-0.2682***	0.0340***	-0.0000***	-54.1386***	0.4184
	ENG	1.4404***	3.9176***	-0.1316 ***	-0.3366***	-0.2865***	-0.0001***	-111.7049***	0.1208
		0.2858***	-1.4266***	0.0644***	0.2208***	0.0629***	0.0001***	160.3959***	0.2280
		1.1772***	-1.1397***	0.0249***	-0.0931***	0.0461***	-0.0001***	-123.8687***	0.4444
	SAB	2.6993***	5.0524***	0.1226*	-0.7231***	-0.5268***	-0.0000***	-327.5806***	0.0991
		0.1842***	-4.7799***	0.0239**	0.7983***	0.3493***	0.0000***	269.8147***	0.2026
		1.0003***	-0.5593***	-0.1240***	-0.1958***	-0.1501***	-0.0000***	-77.3537***	0.2715
	REE	2.3707***	2.2267***	-0.1925***	-0.3597**	-0.2960***	-0.0003***	-220.5678***	0.2058
		0.1078***	-0.4672	0.0362***	0.1659***	0.0165***	0.0002***	148.9547***	0.2921
		0.8858***	0.1405	0.0169***	-0.1448***	0.0736***	-0.0001***	-72.3259***	0.4636

Table 3. Panels A–C report, respectively, random-effects meta-analytic coefficients (inverse-variance weighting across stock-level OLS), the share of Mid-Cap stocks with significant positive/negative coefficients for lagged VPIN, and individual stock regressions with heteroskedasticity-consistent (MacKinnon–White) standard errors. All variables are winsorized at the 1st/99th percentiles within stock. All specifications include lagged controls (CRASH, SSB, DECAL, SIZE, VOLATILITY). *, **, and *** denote statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

conclusions concerning market instability, regulatory effects, and adverse selection dynamics.

Collectively, the panel robustness checks lend additional credibility to our primary meta-analytic results, underscoring the nuanced impact of informed trading across firm size groups and affirming the validity and reliability of our empirical strategy.

4.2. Joint conditional probability results

To test Hypothesis 2 (H2)—that belief dispersion is a better predictor of market volatility than informed trading—we employ Conditional Probability Tables (CPTs), presented by capitalization (Tables 6–8). This approach is highly effective in representing the complex, non-linear associations between our variables, as the LOB's state reflects latent trader intentions, not just executed trades.

Table 4
Non-contemporaneous relationship between consensus, liquidity, and informed trading in Small Cap.

PANEL A Meta-analytic coefficient for 10 individual regressions of small-cap stocks

SMALL CAP	$VPIN_{\tau-1}$	$CRASH_{\tau-1}$	$SSB_{\tau-1}$	$DECAL_{\tau-1}$	$SIZE_{\tau-1}$	$VOLATILITY_{\tau-1}$
SLOPE	0.6208***	-0.0000***	-0.2946***	-0.0801**	-0.0000***	-146.1467***
	(0.1625)	(0.0000)	(0.0410)	(0.0378)	(0.0000)	(23.5091)
RS	0.3079	0.0000***	0.6945***	0.0668	0.0001***	210.6149***
	(0.3850)	(0.0000)	(0.0625)	(0.0454)	(0.0000)	(33.7739)
DEPTH	-1.1891***	-0.0000***	-0.2140***	0.0096	-0.0000***	-49.9929***
	(0.2262)	(0.0000)	(0.0201)	(0.0230)	(0.0000)	(10.1243)

PANEL B Percentage of small-cap stocks with significant effects (lagged VPIN)

SMALL CAP	*% Positive Significant*	*% Positive Non-significant*	*% Negative Significant*	*% Negative Non-significant*	*N stocks*
SLOPE	60.0 %	10.0 %	0.0 %	30.0 %	10
RS	40.0 %	10.0 %	50.0 %	0.0 %	10
DEPTH	20.0 %	0.0 %	80.0 %	0.0 %	10

PANEL C Individual regressions of small-cap stocks

SLOPE 10^{-3} *RS* 10^{3} *DEPTH* 10^{-2}		*C*	$VPIN_{\tau-1}$	$CRASH_{\tau-1}$	$SSB_{\tau-1}$	$DECAL_{\tau-1}$	$SIZE_{\tau-1}$	$VOLATILITY_{\tau-1}$	*ADJ* R^2
SMALL CAP	MRL	1.1242***	0.5911***	-0.0326***	-0.1660***	0.0064	-0.0000***	-1122516***	0.1298
		0.4876**	-0.8183***	0.0554***	0.4831***	-0.0548***	0.0000***	237.6552***	0.1846
		1.0321***	-1.5530**	-0.0542***	-0.1950***	0.0459***	-0.0001***	-59.4654 ***	0.1846
	COL	1.3432***	-0.7119***	-0.0000***	-0.1248***	0.0553***	-0.0001***	-98.9803***	0.0995
		0.4778***	1.6236***	0.0000***	0.4152**	0.0265	0.0003***	83.8091***	0.0611
		0.8544***	-1.3703***	-0.0000***	-0.1625***	0.0841***	-0.0001***	-36.9042***	0.2071
	IDR	1.0263***	0.5038***	-0.0934***	-0.1458***	-0.0692***	-0.0000***	-110.5197***	0.1088
		0.5249***	-1.0266***	0.1322***	0.5028***	0.0801***	0.0000***	309.4739***	0.1858
		0.9284***	0.0990***	-0.0094***	-0.1700***	0.0528***	-0.0000***	-93.8142***	0.3367
	MEL	-0.2908***	1.0654***	-0.1806***	-0.6547***	-0.3113***	-0.0000	-313.6903***	0.0754
		-0.0753***	0.9129***	0.2036***	0.5976***	0.0048	0.0001***	314.1435***	0.2569
		0.5498***	0.1576***	-0.0537***	-0.1472***	-0.0491***	-0.0000***	-30.3194***	0.2785
	ACX	2.3561***	-1.0486	-0.1218***	-0.3271***	-0.1602***	-0.0001***	-192.3845***	0.1037
		-0.0143	2.3770***	0.1571***	0.7561***	0.0686***	0.0002***	132.6497***	0.2369
		0.6891***	-0.9598***	-0.0479***	-0.2798***	0.0187***	-0.0001***	0.8307	0.2588
	CIE	0.7482***	0.3235	-0.0411***	-0.2052***	0.0082	-0.0001	-15.9699***	0.0945
		0.4528***	1.3897	0.2719***	0.9767***	0.0197	0.0011***	114.5307***	0.1793
		0.9119***	-0.4936***	-0.0510***	-0.2934***	0.0041	-0.0007***	-29.4452***	0.4557
	VIS	0.8750***	1.1660***	-0.0977***	-0.2610**	-0.2103**	-0.0000***	-101.3427***	0.1926
		0.5931***	-1.3896***	0.2305***	0.8218***	0.2410***	0.0002***	240.5042***	0.2158
		0.8701***	-0.8653***	-0.0207***	-0.2106***	0.0623***	-0.0001***	-52.9097***	0.4134
	BKIA	2.1377***	1.1226***	-0.1289***	-0.4660***	-0.2423***	-0.0000***	-295.6082***	0.1104
		0.0615**	-1.0411***	0.1933***	0.9628***	0.2965***	0.0000***	339.2383***	0.2685
		0.8257***	-0.4040***	-0.0236***	-0.2481***	-0.1107***	-0.0000***	-43.9252***	0.3596
	ANA	1.0107***	1.2755***	-0.0910***	-0.2015***	0.0788***	-0.0000***	-65.4014***	0.0386
		0.4549***	-1.2271***	0.2320***	0.6867***	-0.0480**	0.0000***	266.0730***	0.1638
		1.1785***	-1.3554***	-0.0242***	-0.0771***	-0.0134***	-0.0000***	-113.0781***	0.4044
	SGRE	2.2220***	-1.2092	0.1490***	-0.3694***	0.0407	-0.0004***	-153.8551***	0.1255
		-0.1106	5.2945***	-0.0340*	0.6919***	-0.0066	0.0006***	87.3432***	0.2018
		1.2783***	-5.9232***	-0.0418***	-0.3462***	0.0062	-0.0002***	-40.9050***	0.3664

Table 4. Panels A–C report, respectively, random-effects meta-analytic coefficients (inverse-variance weighting across stock-level OLS), the share of Small-Cap stocks with significant positive/negative coefficients for lagged VPIN, and individual stock regressions with heteroskedasticity-consistent (MacKinnon–White) standard errors. All variables are winsorized at the 1st/99th percentiles within stock. All specifications include lagged controls (CRASH, SSB, DECAL, SIZE, VOLATILITY). *, **, and *** denote statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

We adopt a normalized approach, expressing both consensus and informed trading as stock-by-stock empirical cumulative distribution functions (CDFs) to enhance comparability. Concretely, VPIN (CDF) proxies for informed trading (where high values indicate greater order-flow toxicity), and SLOPE (CDF) proxies for LOB consensus (where high values indicate greater belief consensus).

For the dependent variable, we employ conditional volatility estimated via an EGARCH (1,1) model. This specification aptly captures the asymmetric dynamics and clustering prominent in high-frequency data, offering a forward-looking, model-based measure that is less sensitive to outliers or microstructure noise than simple realized or absolute return-based proxies.

To ensure statistical validity, we apply two advanced resampling techniques. First, we implement bootstrapping of the CPTs (5000 resamples) to generate empirical confidence intervals (CIs) for each estimated probability, quantifying the statistical uncertainty of the observed joint distributions. Second, we conduct Monte Carlo simulations (10,000 tables) to benchmark our observed CPTs against the null hypothesis of independence, allowing us to identify statistically significant deviations.

The results provide strong evidence for H2 across all capitalization segments. As shown in Panel A of each table, a strong,

Table 5
Fixed Effects Panel (Driscoll-Kraay) controlled by average traded size and conditional volatility.

	$VPIN_{\tau-1}$	$CRASH_{\tau-1}$	$SSB_{\tau-1}$	$DECAL_{\tau-1}$	$SIZE_{\tau-1}$	$VOLATILITY_{\tau-1}$	R^2
Panel A. Large Cap fixed effects panel with Driscoll-Kraay covariance, winsorized variables, robust to serial, cross-sectional and heteroskedastic dependence							
SLOPE	1.8758**	-0.1771**	-0.4516***	-0.4738***	-7.357e-05***	-243.33***	0.1509
	(0.7307)	(0.0723)	(0.0759)	(0.0618)	(0.0000)	(026.243)	
RS	0.1006	0.0209	0.2049***	0.0166	2.649e-05***	126.25***	0.2311
	(0.2683)	(0.0142)	(0.0669)	(0.0124)	(0.0000)	(12.534)	
DEPTH	-1.5395***	0.0028	-0.1718***	0.0434**	-1.242e-05***	-85.753***	0.2527
	(0.4087)	(0.0392)	(0.0263)	(0.0180)	(0.0000)	(8.5510)	
Panel B. Mid Cap fixed effects panel with Driscoll-Kraay covariance, winsorized variables, robust to serial, cross-sectional and heteroskedastic dependence							
SLOPE	-1.1668	0.0194	-0.3812***	-0.2039***	-8.882e-06***	-214.80***	0.0941
	(0.8343)	(0.0811)	(0.0585)	(0.0432)	(0.0000)	(26.452)	
RS	0.0309	0.0046	0.4894***	0.0736**	1.6e-05***	233.05***	0.2127
	(0.7743)	(0.0381)	(0.1159)	(0.0269)	(0.0000)	(21.150)	
DEPTH	-0.6693***	-0.0151	-0.1013***	0.0181	-3.635e-06***	-88.492***	0.2586
	(0.1789)	(0.0218)	(0.0203)	(0.0134)	(0.0000)	(6.6041)	
Panel C. Small Cap fixed effects panel with Driscoll-Kraay covariance, winsorized variables, robust to serial, cross-sectional and heteroskedastic dependence							
SLOPE	0.7093*	-0.1080**	-0.3737***	-0.1482***	-0.0000***	-157.6600***	0.0640
	(0.3633)	(0.0527)	(0.0309)	(0.0300)	(0.0000)	(12.8850)	
RS	-0.3336	0.1725***	0.7111***	0.1059*	0.0000***	246.0400***	0.2051
	(0.3100)	(0.0645)	(0.1079)	(0.0587)	(0.0000)	(58.5860)	
DEPTH	-0.8879***	-0.0402	-0.1909***	-0.0050	-0.0000***	-51.1500***	0.2936
	(0.1861)	(0.0270)	(0.0124)	(0.0193)	(0.0000)	(5.8598)	

Table 5. Fixed-effects panel regressions with Driscoll–Kraay robust covariance (entity fixed effects). Dependent variables are *SLOPE*, *RS*, and *DEPTH*. All variables are winsorized at the 1st/99th percentiles within stock. All specifications include lagged controls (*CRASH*, *SSB*, *DECAL*, *SIZE*, *VOLATILITY*). *, **, and *** denote statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

monotonic relationship exists between SLOPE (CDF) and a reduction in subsequent volatility. We find that high values of SLOPE (CDF) are consistently associated with lower subsequent volatility, indicating that greater investor consensus acts as a stabilizing force. This stabilizing effect is most pronounced for large-cap stocks (Table 6, Panel A). The relationship is exceptionally strong: as consensus (SLOPE CDF) rises above the 0.3 threshold, the probability of observing the lowest volatility state exceeds 93 % and approaches unity (over 97 %) at the highest consensus levels, completely eliminating tail risk.

For small-cap stocks (Table 8, Panel A), the predictive role of market consensus SLOPE CDF on volatility is particularly strong and clear. The conditional probability table shows that as consensus increases, the probability of observing low conditional volatility rises steeply, while the likelihood of moderate or high volatility essentially vanishes. Specifically, when SLOPE CDF is between 0.1 and 0.3, the probability of very low volatility rises above 50 %, and for SLOPE CDF in the range 0.5–0.8, it surpasses 67 %, peaking above 71 % for the very highest consensus levels. For mid-cap stocks (Table 7, Panel A), it is also economically meaningful, though less pronounced. In this group, the probability of low volatility steadily increases from 10 % in the bottom decile to over 57 % in the top decile.

In sharp contrast, VPIN (CDF) displays a weaker and less systematic relationship with volatility; its predictive power for future volatility is inferior to that of the consensus measure as shown in Panel B of each table. For Large, Mid, and Small caps alike, the conditional probability distributions for volatility remain flat across all VPIN (CDF) percentiles. The relationship is not monotonic, and transitions between bins do not signal a reliable shift in volatility. Even at the highest percentiles of VPIN, where market toxicity is expected to peak, the probability of high volatility remains low and the shifts are small and irregular.

These findings are statistically robust to both our bootstrapping and Monte Carlo simulations, with the observed relationships remaining statistically significant and well outside the range of outcomes generated under the null of independence. Furthermore, the superiority of SLOPE (CDF) as a volatility predictor remains fully consistent when using an alternative volatility specification (absolute return residuals).[6]

Collectively, this analysis provides strong evidence for H2. Market consensus, as captured by the normalized slope of the LOB, systematically and robustly predicts lower future volatility across all capitalization groups. Belief dispersion in the order book—not the toxicity of executed order flow—is the key forward-looking determinant of short-term market stability.

4.3. *Informed trading, consensus and volatility causality*

While a considerable body of literature has examined the association between volatility and informativeness—both at the aggregate and order-book levels (Easley et al., 2011; Hoechle, 2007)— most prior studies have emphasized unconditional or contemporaneous relations, leaving causal directionality and persistence underexplored. In particular, the causal interplay among informed trading, belief dispersion, and volatility remains insufficiently mapped, especially regarding the latent intentions embedded

[6] Full details and robustness tables are available upon request.

Table 6
Conditional probability distributions of volatility based on the consensus of the LOB and informed trading in Large Cap.

Panel A. CDF of slope of the LOB.

Categories of SLOPE (CDF) \ Categories of Conditional Volatility	0.00% - 0.46%	0.46% - 0.91%	0.91% - 1.36%	1.36% - 1.8%	1.8% - 2.25%	2.25% - 2.7%	2.7% - 3.14%	3.14% - 3.59%	3.59% - 4.04%	4.04% - 4.48%
0.0 - 0.05	0.6420	0.2861	0.0622	0.0091	0.0002	0.0002	0.0001	0.0001	0.0001	0.0001
0.05 - 0.1	0.8433	0.1434	0.0120	0.0013	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
0.1 - 0.15	0.9054	0.0879	0.0060	0.0008	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
0.15 - 0.2	0.9350	0.0610	0.0036	0.0005	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
0.2 - 0.25	0.9255	0.0686	0.0054	0.0005	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
0.25 - 0.3	0.9244	0.0712	0.0035	0.0008	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
0.3 - 0.35	0.9569	0.0405	0.0024	0.0002	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
0.35 - 0.4	0.9741	0.0248	0.0011	0.0001	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
0.4 - 0.45	0.9819	0.0171	0.0011	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
0.45 - 0.5	0.9845	0.0150	0.0005	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
0.5 - 0.55	0.9861	0.0133	0.0006	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
0.55 - 0.6	0.9820	0.0174	0.0006	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
0.6 - 0.65	0.9807	0.0187	0.0005	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
0.65 - 0.7	0.9753	0.0241	0.0006	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
0.7 - 0.75	0.9715	0.0273	0.0012	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
0.75 - 0.8	0.9644	0.0347	0.0010	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
0.8 - 0.85	0.9574	0.0421	0.0005	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
0.85 - 0.9	0.9727	0.0269	0.0003	0.0001	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
0.9 - 0.95	0.9739	0.0254	0.0007	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
0.95 - 1.0	0.9800	0.0190	0.0010	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Panel B. CDF of VPIN.

Categories of VPIN (CDF) \ Categories of Conditional Volatility	0.00% - 0.46%	0.46% - 0.91%	0.91% - 1.36%	1.36% - 1.8%	1.8% - 2.25%	2.25% - 2.7%	2.7% - 3.14%	3.14% - 3.59%	3.59% - 4.04%	4.04% - 4.48%
0.0 - 0.05	0.9509	0.0472	0.0019	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
0.05 - 0.1	0.9518	0.0457	0.0024	0.0001	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
0.1 - 0.15	0.9486	0.0492	0.0019	0.0003	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
0.15 - 0.2	0.9481	0.0482	0.0034	0.0004	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
0.2 - 0.25	0.9467	0.0506	0.0022	0.0005	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
0.25 - 0.3	0.9473	0.0490	0.0030	0.0007	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
0.3 - 0.35	0.9443	0.0516	0.0034	0.0008	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
0.35 - 0.4	0.9410	0.0545	0.0044	0.0002	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
0.4 - 0.45	0.9430	0.0525	0.0044	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
0.45 - 0.5	0.9426	0.0525	0.0043	0.0005	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
0.5 - 0.55	0.9379	0.0559	0.0056	0.0006	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
0.55 - 0.6	0.9365	0.0562	0.0067	0.0006	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
0.6 - 0.65	0.9357	0.0584	0.0050	0.0009	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
0.65 - 0.7	0.9377	0.0551	0.0065	0.0007	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
0.7 - 0.75	0.9376	0.0548	0.0067	0.0008	0.0001	0.0000	0.0001	0.0000	0.0000	0.0000
0.75 - 0.8	0.9407	0.0509	0.0074	0.0008	0.0000	0.0001	0.0000	0.0000	0.0000	0.0000
0.8 - 0.85	0.9408	0.0522	0.0063	0.0005	0.0000	0.0000	0.0000	0.0001	0.0000	0.0000
0.85 - 0.9	0.9278	0.0645	0.0073	0.0005	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
0.9 - 0.95	0.9330	0.0546	0.0107	0.0015	0.0001	0.0001	0.0000	0.0000	0.0000	0.0000
0.95 - 1.0	0.9249	0.0606	0.0118	0.0026	0.0000	0.0000	0.0000	0.0001	0.0000	0.0001

Color Scale Legend (Probability): 0 – 0.5 – 1

Table 6. Panels A and B show conditional probability distributions of volatility at bucket τ based on SLOPE CDF and VPIN CDF at bucket τ–1 in large-cap stocks.

in unexecuted orders that constitute a substantial share of the LOB activity.

Understanding these causal dynamics is essential for academic theory as well as for practice in risk management and regulatory oversight, as it aids in the early identification of destabilizing conditions and informational shocks. Our study aims to fill this gap by rigorously investigating the temporal and causal relationships among informed trading, LOB consensus formation, and high-frequency volatility.

To map the causal interplay and feedback dynamics among the three, we adopt a stock-by-stock Vector Autoregressive (VAR) framework which is well-suited to capturing rich feedback dynamics and potential endogeneity in high-frequency financial markets (Baruník et al., 2020; Hasbrouck, 2007).

Table 7
Conditional probability distributions of volatility based on the consensus of the LOB and informed trading in Mid Cap.

Panel A. CDF of slope of the LOB.

Categories of SLOPE (CDF)	0.00% - 0.23%	0.23% - 0.41%	0.41% - 0.59%	0.59% - 0.77%	0.77% - 0.95%	0.95% - 1.13%	1.13% - 1.31%	1.31% - 1.49%	1.49% - 1.67%	1.67% - 1.85%
0.0 - 0.05	0.1030	0.5088	0.2726	0.0900	0.0180	0.0065	0.0003	0.0005	0.0004	0.0000
0.05 - 0.1	0.2107	0.6238	0.1307	0.0288	0.0042	0.0014	0.0002	0.0002	0.0001	0.0000
0.1 - 0.15	0.2945	0.6074	0.0790	0.0155	0.0025	0.0008	0.0000	0.0002	0.0000	0.0000
0.15 - 0.2	0.3180	0.6129	0.0582	0.0090	0.0014	0.0003	0.0001	0.0002	0.0000	0.0000
0.2 - 0.25	0.3592	0.5872	0.0454	0.0071	0.0006	0.0003	0.0000	0.0000	0.0000	0.0001
0.25 - 0.3	0.4160	0.5428	0.0341	0.0060	0.0007	0.0004	0.0000	0.0000	0.0000	0.0000
0.3 - 0.35	0.4337	0.5252	0.0342	0.0056	0.0011	0.0003	0.0000	0.0000	0.0000	0.0000
0.35 - 0.4	0.4328	0.5328	0.0291	0.0046	0.0005	0.0002	0.0000	0.0000	0.0001	0.0000
0.4 - 0.45	0.4289	0.5380	0.0272	0.0050	0.0006	0.0002	0.0000	0.0000	0.0001	0.0000
0.45 - 0.5	0.4115	0.5582	0.0263	0.0035	0.0004	0.0001	0.0001	0.0000	0.0000	0.0000
0.5 - 0.55	0.4398	0.5353	0.0219	0.0027	0.0004	0.0001	0.0000	0.0000	0.0000	0.0000
0.55 - 0.6	0.4827	0.4980	0.0171	0.0017	0.0005	0.0001	0.0000	0.0000	0.0000	0.0000
0.6 - 0.65	0.5395	0.4449	0.0133	0.0019	0.0002	0.0001	0.0001	0.0001	0.0000	0.0000
0.65 - 0.7	0.5576	0.4240	0.0157	0.0019	0.0004	0.0004	0.0001	0.0000	0.0000	0.0000
0.7 - 0.75	0.5401	0.4394	0.0166	0.0030	0.0005	0.0003	0.0000	0.0000	0.0000	0.0000
0.75 - 0.8	0.5455	0.4327	0.0167	0.0040	0.0005	0.0005	0.0000	0.0001	0.0000	0.0000
0.8 - 0.85	0.5784	0.3990	0.0177	0.0040	0.0005	0.0004	0.0000	0.0000	0.0000	0.0000
0.85 - 0.9	0.5781	0.3982	0.0196	0.0035	0.0005	0.0000	0.0001	0.0000	0.0000	0.0000
0.9 - 0.95	0.5139	0.4631	0.0201	0.0025	0.0003	0.0000	0.0000	0.0001	0.0000	0.0000
0.95 - 1.0	0.3630	0.6181	0.0174	0.0013	0.0001	0.0001	0.0000	0.0000	0.0000	0.0000

Categories of Conditional Volatility

Panel B. CDF of VPIN.

Categories of VPIN (CDF)	0.00% - 0.23%	0.23% - 0.41%	0.41% - 0.59%	0.59% - 0.77%	0.77% - 0.95%	0.95% - 1.13%	1.13% - 1.31%	1.31% - 1.49%	1.49% - 1.67%	1.67% - 1.85%
0.0 - 0.05	0.4471	0.4932	0.0468	0.0112	0.0011	0.0001	0.0001	0.0002	0.0002	0.0001
0.05 - 0.1	0.4326	0.5173	0.0412	0.0077	0.0011	0.0001	0.0001	0.0000	0.0000	0.0000
0.1 - 0.15	0.4184	0.5301	0.0405	0.0091	0.0013	0.0005	0.0001	0.0000	0.0000	0.0000
0.15 - 0.2	0.4055	0.5452	0.0392	0.0077	0.0017	0.0004	0.0001	0.0001	0.0001	0.0000
0.2 - 0.25	0.4052	0.5419	0.0439	0.0076	0.0010	0.0003	0.0001	0.0000	0.0000	0.0000
0.25 - 0.3	0.4092	0.5377	0.0440	0.0078	0.0012	0.0002	0.0000	0.0000	0.0000	0.0000
0.3 - 0.35	0.4197	0.5287	0.0412	0.0081	0.0016	0.0006	0.0000	0.0000	0.0000	0.0000
0.35 - 0.4	0.4197	0.5297	0.0408	0.0084	0.0010	0.0004	0.0000	0.0000	0.0000	0.0000
0.4 - 0.45	0.4160	0.5326	0.0423	0.0075	0.0009	0.0004	0.0002	0.0001	0.0001	0.0000
0.45 - 0.5	0.4298	0.5207	0.0387	0.0089	0.0015	0.0003	0.0001	0.0000	0.0000	0.0000
0.5 - 0.55	0.4301	0.5148	0.0428	0.0093	0.0018	0.0008	0.0001	0.0003	0.0000	0.0000
0.55 - 0.6	0.4281	0.5169	0.0427	0.0090	0.0027	0.0005	0.0000	0.0001	0.0000	0.0000
0.6 - 0.65	0.4351	0.5064	0.0446	0.0110	0.0020	0.0005	0.0003	0.0000	0.0000	0.0000
0.65 - 0.7	0.4342	0.5070	0.0441	0.0121	0.0017	0.0008	0.0000	0.0001	0.0001	0.0000
0.7 - 0.75	0.4349	0.5113	0.0392	0.0116	0.0022	0.0007	0.0000	0.0001	0.0001	0.0000
0.75 - 0.8	0.4390	0.5031	0.0429	0.0116	0.0027	0.0006	0.0000	0.0000	0.0001	0.0000
0.8 - 0.85	0.4451	0.4995	0.0436	0.0088	0.0021	0.0008	0.0000	0.0000	0.0000	0.0000
0.85 - 0.9	0.4460	0.4919	0.0474	0.0118	0.0024	0.0005	0.0001	0.0001	0.0000	0.0000
0.9 - 0.95	0.4350	0.4893	0.0583	0.0155	0.0016	0.0003	0.0001	0.0000	0.0000	0.0000
0.95 - 1.0	0.4156	0.4728	0.0888	0.0168	0.0024	0.0033	0.0001	0.0000	0.0000	0.0000

Categories of Conditional Volatility

Color Scale Legend: 0, 0.5, 1 (Probability)

Table 7. Panels A and B show conditional probability distributions of volatility at bucket τ based on SLOPE CDF and VPIN CDF at bucket τ–1 in mid-cap stocks.

We therefore model three key variables: conditional volatility (EGARCH), LOB consensus (SLOPE), and cumulative informed trading (VPIN CDF). To isolate endogenous dynamics, we residualize each series against contemporaneous aggregate shocks (CRASH, SSB, DECAL dummies) using the Frisch–Waugh–Lovell (FWL) approach and standardize them (z-scores). Prior to estimation, all series were confirmed to be stationary (Augmented Dickey-Fuller/Phillips-Perron tests), all models passed stability criteria, and optimal lag orders were selected via SC/BIC.

Given the high dimensionality of our analysis (32 stocks, three variables, differing lags), reporting the full set of coefficients is neither practical nor informative. Instead, we adopt a synthesis strategy focusing on two primary outputs. First, to assess causal directionality, we use stock-level Granger Causality tests (Table 9) and aggregate them using panel-level p-value combination (Fisher/

Table 8
Conditional probability distributions of volatility based on the consensus of the LOB and informed trading in Small Cap.

Panel A. CDF of slope of the LOB.

Categories of SLOPE (CDF)	0.00% - 0.27%	0.27% - 0.48%	0.48% - 0.68%	0.68% - 0.89%	0.89% - 1.1%	1.1% - 1.3%	1.3% - 1.51%	1.51% - 1.71%	1.71% - 1.92%	1.92% - 2.12%
0.0 - 0.05	0.2613	0.4705	0.1852	0.0562	0.0208	0.0043	0.0011	0.0001	0.0004	0.0002
0.05 - 0.1	0.4541	0.4238	0.0998	0.0179	0.0036	0.0008	0.0002	0.0000	0.0000	0.0000
0.1 - 0.15	0.5202	0.3904	0.0729	0.0126	0.0032	0.0005	0.0002	0.0000	0.0000	0.0000
0.15 - 0.2	0.5582	0.3708	0.0593	0.0097	0.0016	0.0002	0.0002	0.0000	0.0000	0.0000
0.2 - 0.25	0.5917	0.3398	0.0605	0.0063	0.0011	0.0006	0.0001	0.0000	0.0000	0.0000
0.25 - 0.3	0.6391	0.3075	0.0483	0.0042	0.0007	0.0001	0.0002	0.0001	0.0000	0.0000
0.3 - 0.35	0.6319	0.3168	0.0462	0.0039	0.0008	0.0002	0.0000	0.0000	0.0000	0.0000
0.35 - 0.4	0.6089	0.3358	0.0480	0.0053	0.0019	0.0002	0.0000	0.0000	0.0000	0.0000
0.4 - 0.45	0.6474	0.2982	0.0480	0.0054	0.0007	0.0002	0.0001	0.0000	0.0000	0.0000
0.45 - 0.5	0.6999	0.2539	0.0402	0.0054	0.0004	0.0001	0.0001	0.0000	0.0000	0.0000
0.5 - 0.55	0.7262	0.2264	0.0413	0.0051	0.0010	0.0000	0.0000	0.0000	0.0000	0.0000
0.55 - 0.6	0.7132	0.2423	0.0388	0.0048	0.0008	0.0000	0.0000	0.0001	0.0000	0.0000
0.6 - 0.65	0.6915	0.2597	0.0430	0.0054	0.0003	0.0001	0.0000	0.0000	0.0000	0.0000
0.65 - 0.7	0.6844	0.2685	0.0433	0.0035	0.0002	0.0002	0.0000	0.0001	0.0000	0.0000
0.7 - 0.75	0.6863	0.2838	0.0273	0.0021	0.0002	0.0001	0.0000	0.0000	0.0000	0.0000
0.75 - 0.8	0.6701	0.2982	0.0283	0.0030	0.0002	0.0001	0.0001	0.0000	0.0000	0.0000
0.8 - 0.85	0.6407	0.3093	0.0455	0.0035	0.0008	0.0002	0.0001	0.0000	0.0000	0.0000
0.85 - 0.9	0.6186	0.3307	0.0480	0.0021	0.0005	0.0000	0.0000	0.0000	0.0000	0.0000
0.9 - 0.95	0.6755	0.2956	0.0281	0.0007	0.0001	0.0000	0.0000	0.0000	0.0000	0.0000
0.95 - 1.0	0.7148	0.2792	0.0057	0.0002	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Categories of Conditional Volatility

Panel B. CDF of VPIN.

Categories of VPIN (CDF)	0.00% - 0.27%	0.27% - 0.48%	0.48% - 0.68%	0.68% - 0.89%	0.89% - 1.1%	1.1% - 1.3%	1.3% - 1.51%	1.51% - 1.71%	1.71% - 1.92%	1.92% - 2.12%
0.0 - 0.05	0.7102	0.2324	0.0475	0.0059	0.0036	0.0003	0.0000	0.0000	0.0000	0.0000
0.05 - 0.1	0.6904	0.2587	0.0437	0.0056	0.0015	0.0002	0.0000	0.0000	0.0000	0.0000
0.1 - 0.15	0.6893	0.2589	0.0474	0.0034	0.0005	0.0003	0.0002	0.0000	0.0001	0.0000
0.15 - 0.2	0.6686	0.2829	0.0440	0.0036	0.0005	0.0000	0.0001	0.0001	0.0002	0.0001
0.2 - 0.25	0.6682	0.2815	0.0453	0.0045	0.0003	0.0002	0.0000	0.0000	0.0000	0.0000
0.25 - 0.3	0.6530	0.2951	0.0468	0.0041	0.0008	0.0002	0.0000	0.0000	0.0000	0.0001
0.3 - 0.35	0.6484	0.3001	0.0451	0.0046	0.0011	0.0005	0.0001	0.0000	0.0001	0.0000
0.35 - 0.4	0.6416	0.3007	0.0493	0.0064	0.0017	0.0002	0.0001	0.0000	0.0000	0.0000
0.4 - 0.45	0.6343	0.3102	0.0481	0.0053	0.0019	0.0002	0.0000	0.0000	0.0000	0.0000
0.45 - 0.5	0.6307	0.3085	0.0505	0.0074	0.0024	0.0005	0.0000	0.0000	0.0000	0.0000
0.5 - 0.55	0.6232	0.3184	0.0498	0.0065	0.0011	0.0007	0.0002	0.0000	0.0000	0.0000
0.55 - 0.6	0.6183	0.3212	0.0518	0.0073	0.0011	0.0002	0.0000	0.0000	0.0000	0.0000
0.6 - 0.65	0.6172	0.3214	0.0519	0.0084	0.0008	0.0002	0.0000	0.0000	0.0000	0.0000
0.65 - 0.7	0.6080	0.3289	0.0542	0.0079	0.0008	0.0002	0.0000	0.0000	0.0000	0.0000
0.7 - 0.75	0.6032	0.3313	0.0558	0.0077	0.0016	0.0000	0.0004	0.0000	0.0001	0.0000
0.75 - 0.8	0.5868	0.3450	0.0557	0.0112	0.0011	0.0000	0.0002	0.0000	0.0001	0.0000
0.8 - 0.85	0.5785	0.3469	0.0600	0.0117	0.0020	0.0002	0.0001	0.0000	0.0000	0.0000
0.85 - 0.9	0.5610	0.3632	0.0589	0.0121	0.0035	0.0011	0.0002	0.0000	0.0000	0.0000
0.9 - 0.95	0.5322	0.3903	0.0583	0.0126	0.0045	0.0020	0.0003	0.0000	0.0000	0.0000
0.95 - 1.0	0.4709	0.4054	0.0937	0.0213	0.0081	0.0006	0.0001	0.0000	0.0000	0.0000

Categories of Conditional Volatility

Color Scale Legend: 0 – 0.5 – 1 (Probability)

Table 8. Panels A and B show conditional probability distributions of volatility at bucket τ based on SLOPE CDF and VPIN CDF at bucket τ–1 in small-cap stocks.

Stouffer) and heterogeneous panel tests (Table 10). Second, to synthesize the average dynamic response and persistence, we use orthogonalized Impulse-Response Functions (IRFs). We quantify stock-level uncertainty via Monte-Carlo IRF bands, propagate errors to cumulative IRFs (root-sum-of-squares), and then aggregate these cumulative responses by horizon (0−7) using a random-effects meta-analysis (Der Simonian–Laird), reporting meta-means, 95 % CIs (Figs. 2–5) and between-stock heterogeneity (τ^2), along with the number of contributing stocks per horizon.[7]

[7] Full coefficient estimates and diagnostics are available in the supplementary materials.

Table 9
Summary of significant causal relationships between main market variables (Pairwise panel causality tests, 2019–2020).

PAIR	# stocks	Stocks
SLOPE → VPIN CDF	13 / 32	AENA, BKIA, CABK, ENG, IAG, IBE, MAP, MEL, MTS, NTGY, SAB, TEF, VIS
SLOPE → EGARCH	32 / 32	All
VPIN CDF → SLOPE	12 / 32	AENA, BBVA, ANA, ENG, FER, GRF, IAG, IBE, MEL, MTS, SAB, VIS
VPIN CDF→ EGARCH	12 / 32	ACS, AENA, BKIA, CIE, ANA, IAG, IBE, MRL, NTGY, SAB, SAN, VIS
EGARCH → SLOPE	32 / 32	All
EGARCH → VPIN CDF	17 / 32	AMS, BKT, CABK, CIE, ANA, ENG, IAG, IBE, IDR, MEL, MRL, MTS, NTGY, REP, SAB, SGRE, VIS

Table 9. The table reports, for each variable pair, the count of stocks (out of 32) exhibiting a significant causal link (based on a stock-specific Wald test, $p < 0.05$) and lists the corresponding tickers.

Table 10
Panel-level Granger causality: Dumitrescu–Hurlin Z-bar (heterogeneous) and Wald (homogeneous) tests.

Causal → Effect	$\bar{Z}$ (D-H)	Wald χ^2	df	p-value
SLOPE → EGARCH	118.23	2912.57	253	0.0
SLOPE → VPIN CDF	13.08	547.28	253	0.0
EGARCH → SLOPE	623.24	14272.46	253	0.0
EGARCH → VPIN CDF	23.42	779.82	253	0.0
VPIN CDF → SLOPE	17.92	656.15	253	0.0
VPIN CDF → EGARCH	17.90	655.64	253	0.0

Table 10. $\bar{Z}$ (D-H) is the Dumitrescu–Hurlin heterogeneous panel causality test. Wald χ^2 is the joint homogeneous panel causality test. All p-values shown are < 0.001. Complementary tests using Fisher/Stouffer combined p-values (not shown) also yielded p-values < 0.001.

A preliminary event study (Fig. 1) confirmed the SSB was unsuitable for identification and was retained as a control.

The VAR system for each stock is specified as follows:

$$EGARCH_{i,\tau} = \alpha_{1i} + \sum_{j=1}^{p} \beta_{11,j} EGARCH_{i,\tau-j} + \sum_{j=1}^{p} \beta_{12,j} SLOPE_{i,\tau-j} + \sum_{j=1}^{p} \beta_{13,j} \mathrm{CDFVPIN}_{i,\tau-j} + \gamma_1 CRASH_{i,\tau} + \gamma_2 SSB_{i,\tau} + \gamma_3 DECAL_{i,\tau} + \epsilon_{1,i,\tau} \tag{13}$$

$$SLOPE_{i,\tau} = \alpha_{2i} + \sum_{j=1}^{p} \beta_{21,j}\ EGARCH_{i,\tau-j} + \sum_{j=1}^{p} \beta_{22,j} SLOPE_{i,\tau-j} + \sum_{j=1}^{p} \beta_{23,j} \mathrm{CDFVPIN}_{i,\tau-j} + \gamma_4 CRASH_{i,\tau} + \gamma_5 SSB_{i,\tau} + \gamma_6 DECAL_{i,\tau} + \epsilon_{2,i,\tau} \tag{14}$$

$$\mathrm{CDFVPIN}_{i,\tau} = \alpha_{3i} + \sum_{j=1}^{p} \beta_{31,j} EGARCH_{i,\tau-j} + \sum_{j=1}^{p} \beta_{32,j} SLOPE_{i,\tau-j} + \sum_{j=1}^{p} \beta_{33,j} \mathrm{CDFVPIN}_{i,\tau-j} + \gamma_7 CRASH_{i,\tau} + \gamma_8 SSB_{i,\tau} + \gamma_9 DECAL_{i,\tau} + \epsilon_{3,i,\tau} \tag{15}$$

$EGARCH_{i,\tau}$ is the conditional volatility of bucket returns for panel (category) stock i in bucket τ. $SLOPE_{\ i,\tau}$ is current consensus of LOB for panel (category) stock i in bucket τ. $CDFVPIN_{\ i,\tau}$ is cumulative informed trading for panel (category) stock i in bucket τ. $EGARCH_{i,\tau-j}$, $SLOPE_{\ i,\tau-j}$, $CDFVPIN_{\ i,\tau-j}$ are lagged values of the respective variables for stock i (j ranges from 1 to p). $CRASH_{i,\tau}$, $SSB_{i,\tau}$ and $\mathrm{DECAL}_{i,\tau}$ are dummy variables for the COVID-19 crash and short selling ban. α_{ki} is the individual constant for stock i in equation k ($k = 1, 2, 3$). $\epsilon_{k,i,\tau}$ are the error terms for each equation, assumed to be serially uncorrelated. In estimation, we partial out CRASH, SSB and DECAL via FWL before fitting the VAR, which is algebraically equivalent to including them contemporaneously.

The Granger causality analysis reveals a clear causal hierarchy. While panel-level tests (Table 10) confirm strong, systematic, bidirectional links among all variables at the aggregate level (all p-values < 0.001), the stock-level analysis (Table 9) reveals critical heterogeneity. Specifically, we find two unanimous causal links: belief consensus is a universal Granger-cause of volatility (SLOPE → EGARCH, 32/32 stocks), providing strong empirical support for Hypothesis H2. Volatility is a universal Granger-cause of belief consensus (EGARCH → SLOPE, 32/32 stocks). This finding supports a hierarchical structure, where the consensus-to-volatility link is the dominant and most consistent direction of influence. This pattern suggests that episodes of belief alignment or dispersion in the order book serve as reliable precursors to fluctuations in market volatility, in line with theoretical models that emphasize the role of information aggregation and crowd behavior in price formation (Hasbrouck, 2007).

In sharp contrast, all causal links involving VPIN (CDF) are asset-dependent and sporadic, significant in only 12–17 stocks. The feedback loop between informed trading and consensus, for instance, is not a universal dynamic: the causal link from VPIN (CDF) to consensus (SLOPE) is present in only 12 out of 32 stocks, and the reverse direction (SLOPE→ VPIN CDF) is significant in 13. This limited and asymmetric incidence highlights that informational flows and belief synchronization are asset-dependent phenomena, likely influenced by liquidity, trading volume, or idiosyncratic event exposure.

Furthermore, the feedback from volatility to informed trading (EGARCH → VPIN CDF) is also contingent, being significant in only approximately half of the sample (17/32 stocks). This non-universal finding is insightful: it suggests that only under specific market conditions, such as periods of high information asymmetry or market stress, do volatility shocks actively induce a subsequent increase in informed trading activity. This pervasive heterogeneity confirms that while the SLOPE-volatility feedback loop is a fundamental market dynamic, the causal role of VPIN (CDF) is secondary and contingent upon specific market states and stock characteristics.

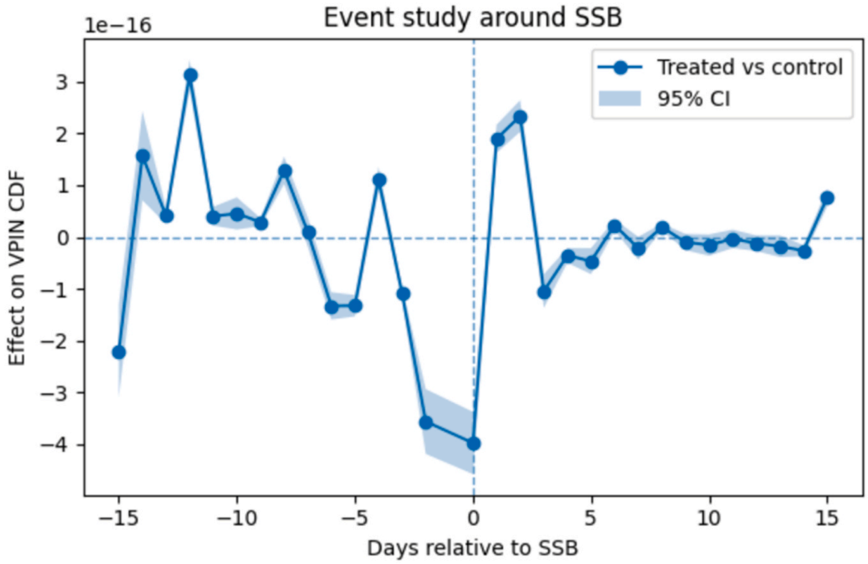

Fig. 1. Event study around short selling ban Fig. 1. Event-study around the short selling ban (SSB). Coefficients are treatment–control differences by period relative to the start period; stock fixed effects and day fixed effects included; shaded area: 95 % CI. Coefficients cluster around zero pre- and post-event.

The meta-analytic IRFs reveal the dynamic nature of these causal links. The aggregate results (Fig. 2) show a robust, asymmetric feedback loop between consensus and volatility: a positive SLOPE shock persistently and significantly lowers subsequent volatility (Panel A), while a positive volatility shock immediately and significantly erodes consensus (Panel B). The impact of VPIN (CDF) is also twofold: it raises conditional volatility (Panel C), but it also leads to a positive and persistent response in SLOPE (Panel E), suggesting that higher adverse selection risk accelerates information assimilation and triggers an adaptive quote realignment that steepens the book.

As this pooled analysis can mask cross-sectional differences, Figs. 3–5 report the stratified analysis by market-capitalization segment. Confidence bands widen from Large to Small caps, reflecting increasing cross-sectional dispersion. For Large Caps (Fig. 3), the microstructure channel is clean: (Panel A) a SLOPE shock lowers conditional volatility, and (Panel B) a volatility shock erodes SLOPE; (Panel C) a VPIN (CDF) shock raises conditional volatility, and (Panel E) it also raises SLOPE. In turn, both (Panel D) higher volatility and (Panel F) higher SLOPE increase VPIN (CDF), generating an amplification feedback loop. Deep books and venue fragmentation help absorb shocks, so magnitudes are moderate even when statistically significant (significance for Slope→VPIN is strongest at intermediate horizons).

For Mid Caps (Fig. 4), the effects are larger and more heterogeneous than in Large Caps. A distinctive feature emerges: a volatility shock causes a negative cumulative response in VPIN (CDF) at medium horizons (Panel D), consistent with informed traders and liquidity providers withdrawing. The stabilizing leg from SLOPE to volatility (Panel A) is also stronger here than in Large Caps, consistent with resiliency being more visible in thinner books. VPIN (CDF) continues to raise Slope (Panel E) and to increase volatility (Panel C), both significantly and persistently.

Finally, for Small Caps (Fig. 5), the dynamic is entirely dominated by the SLOPE-volatility loop, with large and precise estimates (Panels A and B). In this segment, all channels involving VPIN (CDF) are weak and statistically indistinguishable from zero (Panels C-F), likely obscured by thin liquidity and idiosyncratic flows.

Two key takeaways emerge from this causal analysis. First, LOB consensus (SLOPE) is a primary determinant of market stability across the board, as higher SLOPE robustly reduces volatility while volatility, in turn, erodes SLOPE in a persistent feedback loop. Second, the role of VPIN (CDF) is size-contingent, revealing a size-dependent transmission gradient for how information shocks propagate.

In Large Caps, deep books and venue choice allow information shocks to be absorbed. VPIN (CDF) acts as an information signal that creates a modest, bounded amplification loop—raising both SLOPE and volatility—but the pass-through to risk is limited. In Mid Caps, a defense against adverse selection is more visible; VPIN (CDF) still raises volatility and reorganizes the book, but after a volatility spike, informed trading recedes, consistent with a temporary widening of spreads. Finally, in Small Caps, absorption capacity is scarce. The VPIN signal is weak, imprecise, and attenuated, causing the dynamic to be entirely dominated by the SLOPE-volatility loop, where information shocks spill directly into volatility.

Thus, the same informational shock is absorbed in Large Caps, reorganizes the book in Mid Caps, and spills into volatility in Small Caps. These findings argue for asset-specific monitoring. While VPIN and SLOPE should be tracked jointly in Large and Mid Caps to anticipate book reconfiguration and volatility bursts, real-time SLOPE is the more reliable early warning indicator for the Small-Cap segment.

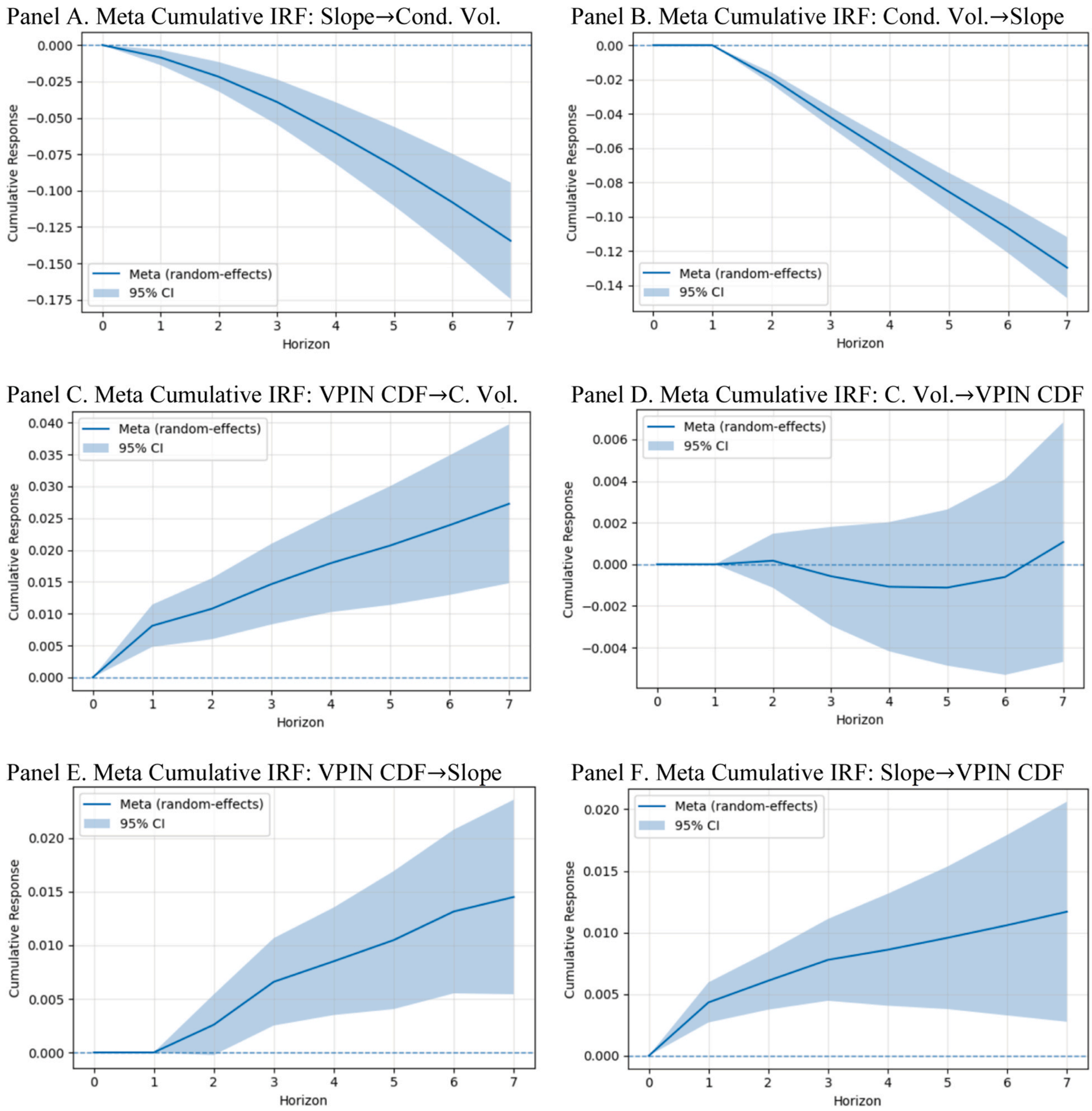

Fig. 2. Meta-analytic Cumulative Impulse Response Functions (IRFs) for the full sample (N = 32). Fig. 2. This figure displays the meta-analytic cumulative impulse response functions (IRFs) for the full sample (N = 32). Lines show the meta-analytic mean, and shaded areas represent the 95 % confidence interval over an 8-period (0–7) horizon.

5. Conclusions

This study investigates the complex interplay between informed trading (VPIN), latent belief consensus in the Limit Order Book (LOB), and short-horizon volatility, using high-frequency, full-book data from the Spanish market during the turbulent 2019–2020 period. Our multifaceted econometric approach—combining meta-analysis, robust panel regressions, conditional probability tables, and VAR modeling—yields a clear and consistent hierarchy of results.

First, we confirm Hypothesis H1, which details the dual, non-contemporaneous role of informed trading. We find VPIN significantly enhances belief consensus (SLOPE), aligning with theories of information-driven order placement, particularly in Large Caps (meta-coefficient 1.4871, $p < 0.05$). However, this positive contribution comes at a cost: VPIN robustly erodes internal liquidity (DEPTH) across all tiers. This trade-off is most acute in Small Caps, which suffer the largest and most consistent erosion of depth (meta-coefficient -1.1891, $p < 0.001$), an effect seen in 80 % of the stocks in that segment.

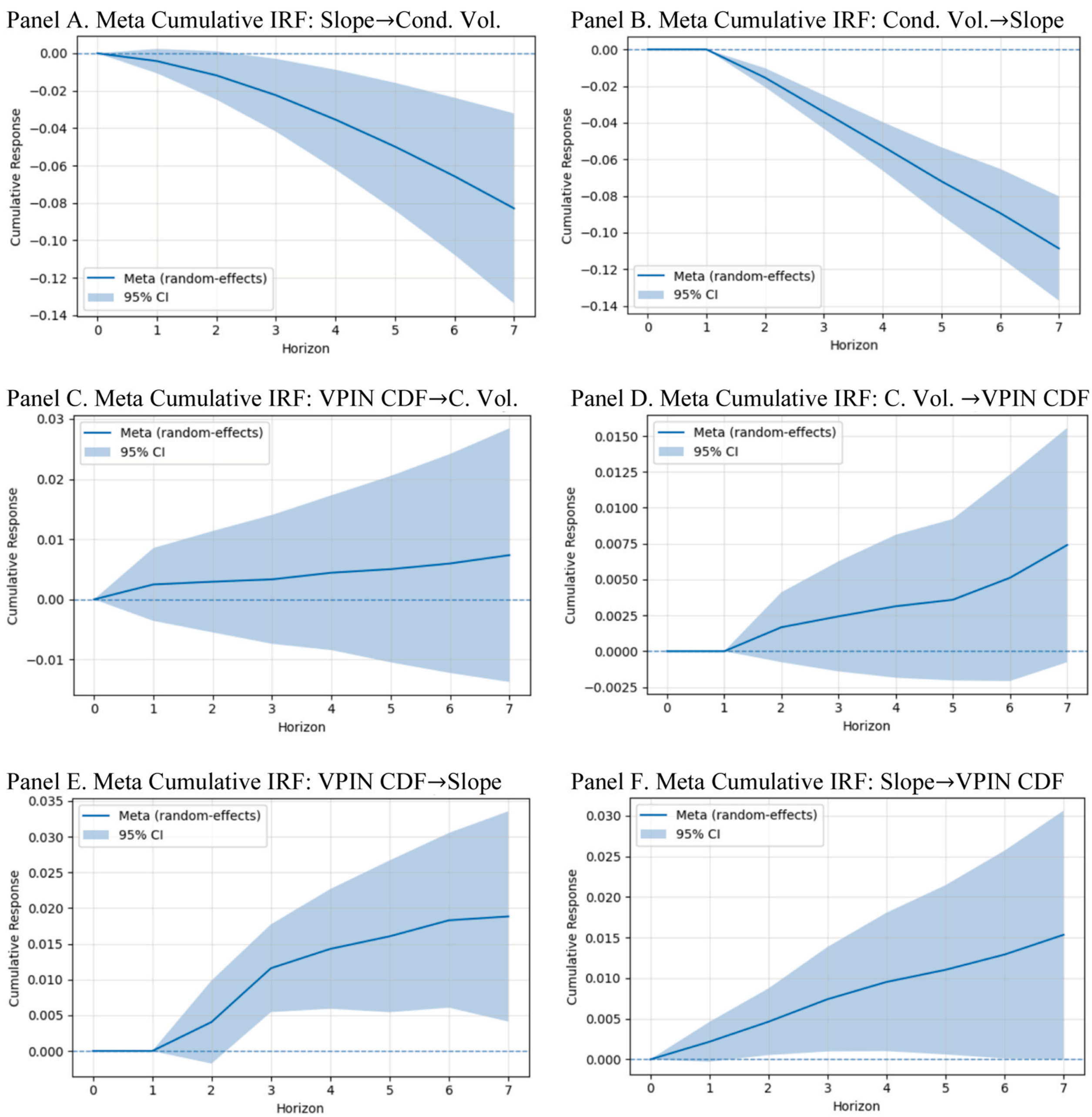

Fig. 3. Meta-analytic Cumulative Impulse Response Functions (IRFs). Large Cap. Fig. 3. This figure displays the meta-analytic cumulative impulse response functions (IRFs) for the large-cap stocks. Lines show the meta-analytic mean, and shaded areas represent the 95 % confidence interval over an 8-period (0−7) horizon.

Second, and most critically, our predictive analysis for Hypothesis H2 provides overwhelming evidence that LOB consensus is a markedly superior forward-looking predictor of volatility than VPIN. This is not a marginal finding; the effect is stark. As SLOPE (CDF) increases, the probability of a subsequent low-volatility state rises monotonically. For Large Caps (Table 6), a high consensus (SLOPE CDF > 0.4) is associated with a > 97 % probability of the market remaining in the lowest-volatility state. This stabilizing effect is universal, with Small Caps (Table 8) also showing a sharp rise in low-volatility probability to > 71 % at high consensus levels. In sharp contrast, the predictive distributions for VPIN (CDF) are flat and provide no meaningful informational content.

Third, our VAR analysis for Hypothesis H3 confirms the causal hierarchy behind these predictions. We uncover a unanimous (32/32 stocks), bidirectional, and asymmetric feedback loop: belief consensus (SLOPE) robustly Granger-causes a reduction in volatility, while volatility, in turn, unanimously erodes belief consensus. The aggregate IRF analysis (Fig. 2) confirms a positive SLOPE shock leads to a persistent, significant decline in volatility. In contrast, all causal links involving VPIN (CDF) are sporadic and asset-

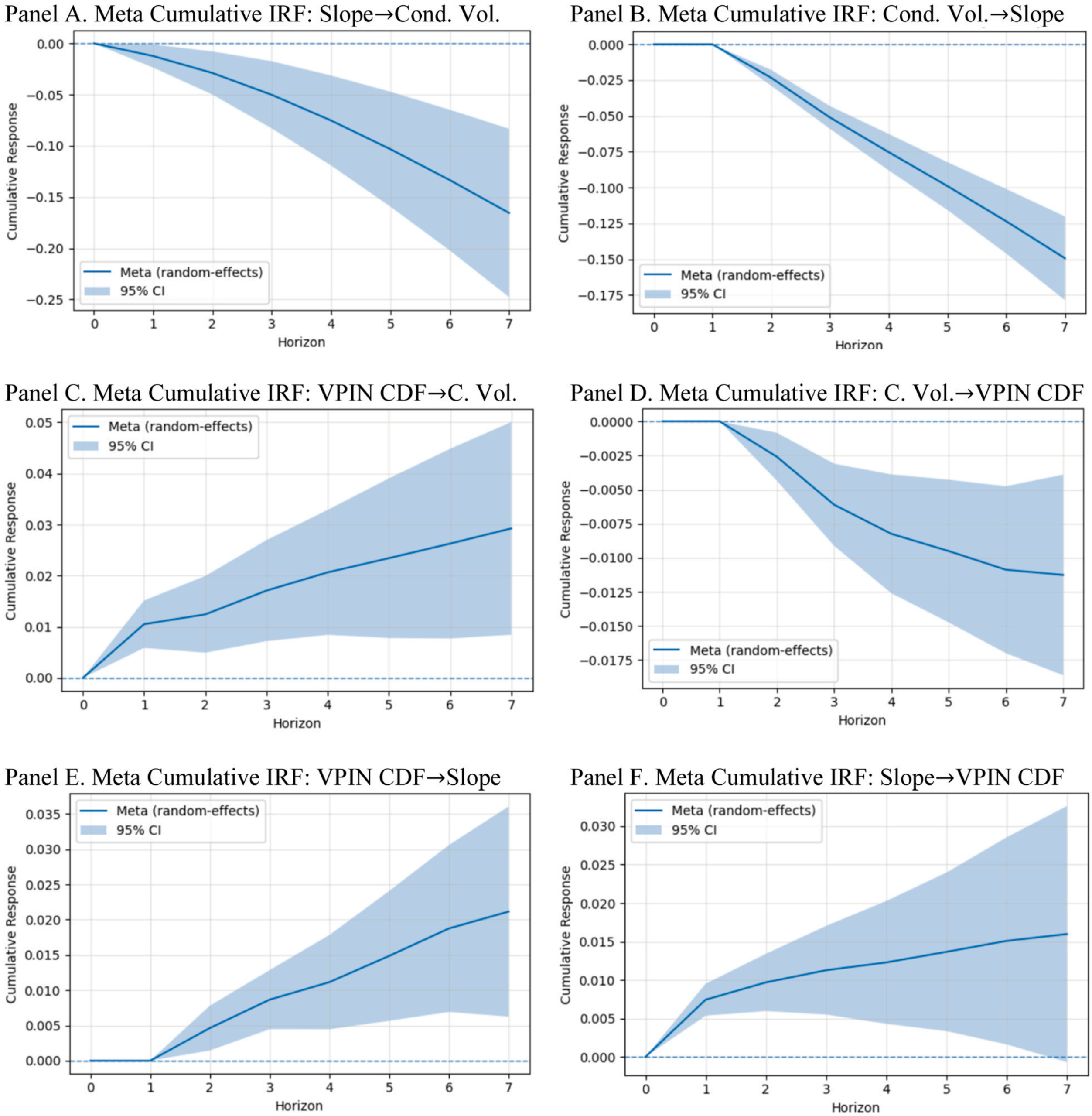

Fig. 4. Meta-analytic Cumulative Impulse Response Functions (IRFs). Mid Cap. Fig. 4. This figure displays the meta-analytic cumulative impulse response functions (IRFs) for the mid-cap stocks. Lines show the meta-analytic mean, and shaded areas represent the 95 % confidence interval over an 8-period (0−7) horizon.

dependent, significant in only 12–17 stocks, reinforcing its secondary and contingent role in risk dynamics.

The central contribution of this paper is a fundamental shift in analytical focus. We challenge the prevailing view centered on realized trade imbalances as the key microstructural determinant of risk. We demonstrate that the latent geometry of the order book (SLOPE)—acting as a proxy for aggregated belief consensus—is the dominant forward-looking stabilizer of short-term volatility. We establish a new informational channel where the structure of latent beliefs, not the flow of trades, is the primary mechanism governing market stability. Our findings also reveal a size-dependent transmission gradient: the same information shock that is absorbed by Large Caps and reorganizes Mid Caps spills directly into volatility for Small Caps.

The implications of these findings are significant. For risk management and regulatory surveillance, our results suggest that monitoring flow toxicity (VPIN) is insufficient. The real-time state of LOB consensus (SLOPE) emerges as a more reliable and universal early warning indicator of market fragility—particularly in the small-cap segment, where the VPIN signal is least reliable.

Finally, we argue that these findings possess a high degree of generalizability. This assertion rests on two distinct pillars. First, our

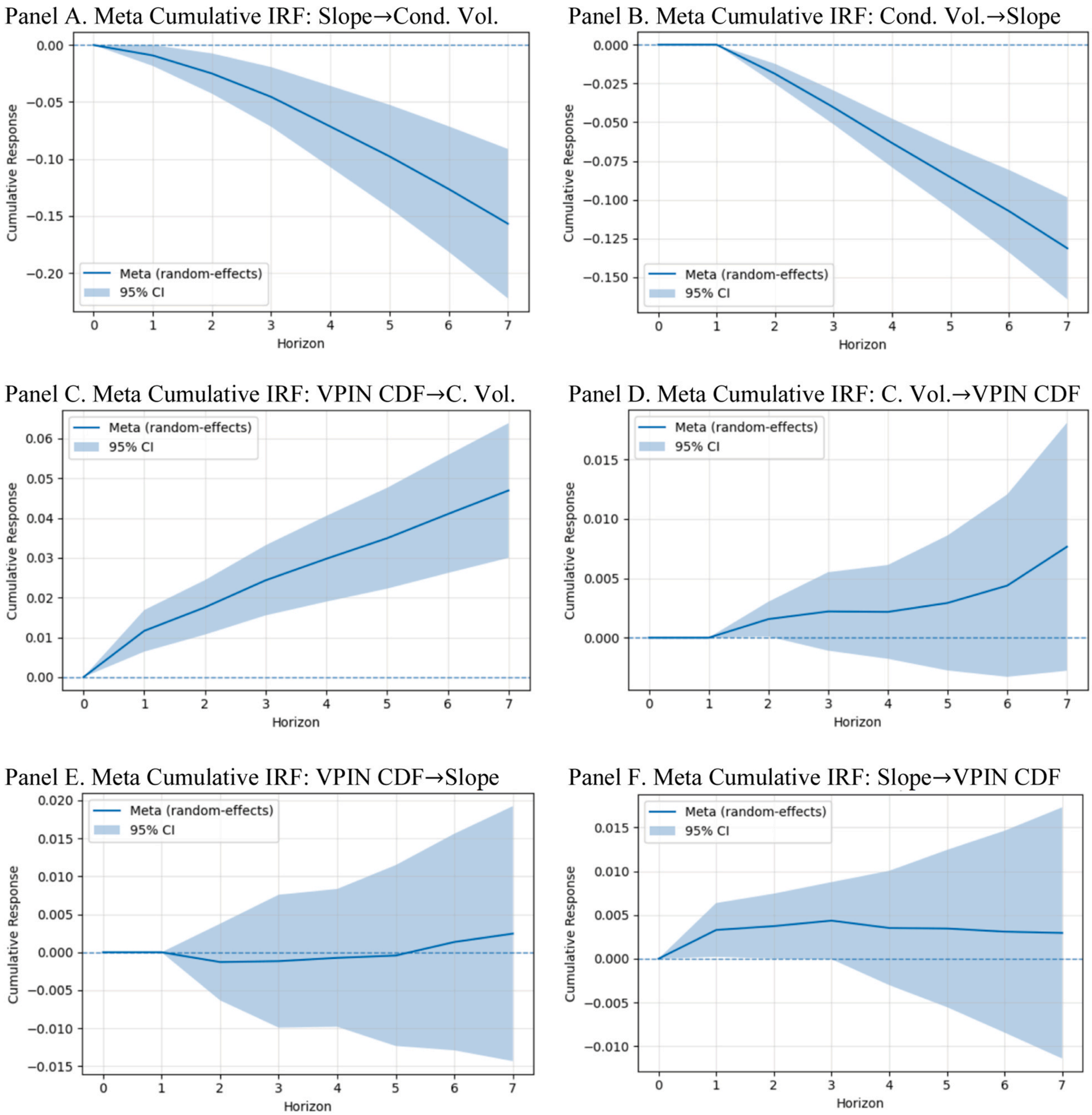

Fig. 5. Meta-analytic Cumulative Impulse Response Functions (IRFs). Small Cap. Fig. 5. This figure displays the meta-analytic cumulative impulse response functions (IRFs) for the small-cap stocks. Lines show the meta-analytic mean, and shaded areas represent the 95 % confidence interval over an 8-period (0−7) horizon.

sample is comprised of the constituents of the IBEX 35, an index dominated by major multinational enterprises (MNEs) whose global operations and valuations are of direct relevance to international investors and corporate financial management. Second, these MNEs trade on the SIBE platform, which possesses high structural equivalence to other major global exchanges (e.g., Euronext, Xetra, LSE) as a standard, electronic, order-driven Central Limit Order Book (CLOB). Therefore, the fundamental microstructure mechanism we uncover—the stabilizing tension between latent belief consensus and volatility—is not a local artifact but a fundamental characteristic of modern market design, tested on a sample of globally relevant firms.

CRediT authorship contribution statement

Martin Daniel: Writing – original draft, Validation, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Sandra Ferreruela:** Writing – review & editing, Resources, Funding acquisition, Conceptualization.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

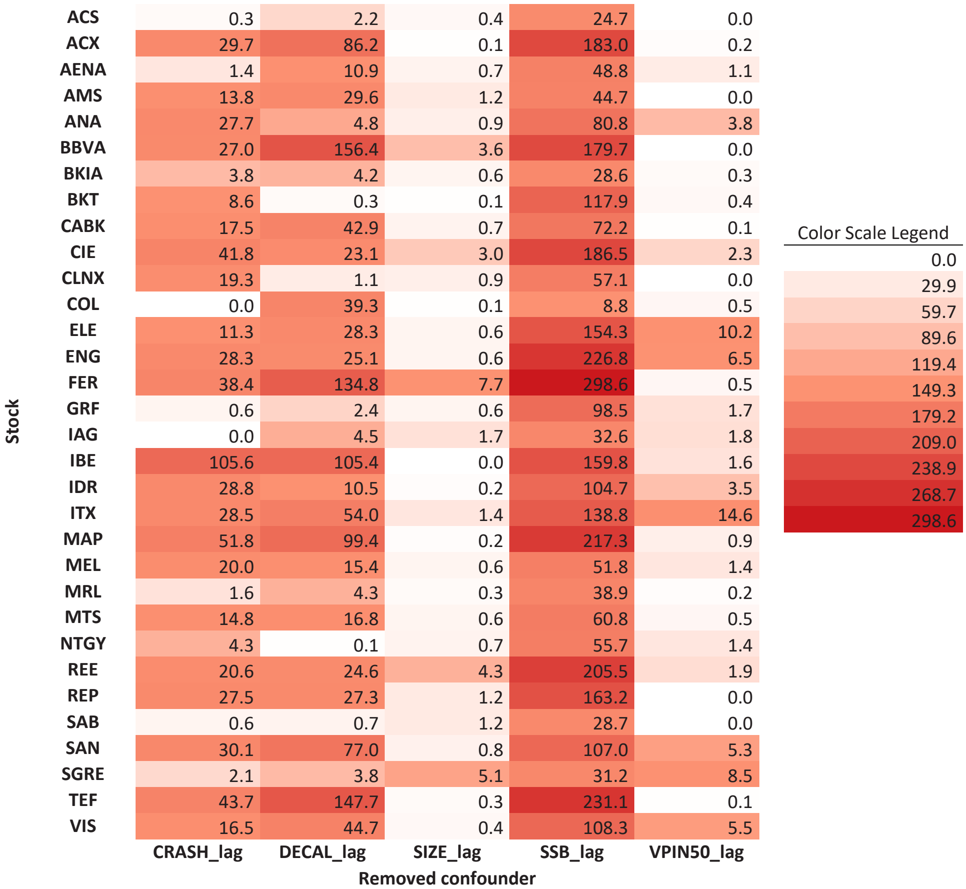

Figure A1. Relative change (%) in the SLOPE coefficient after removing individual confounders

Figure A1. Relative change (%) in the SLOPE coefficient after removing individual confounders in the SLOPE to Conditional Volatility specification. The heatmap displays percentage variations in the estimated coefficient when each confounder is excluded from the model, for each IBEX-35 constituent. Positive values indicate an increase in the SLOPE coefficient upon confounder removal, while negative values (if any) indicate a reduction. Values are centered at zero and color-coded using a diverging “coolwarm” scale, with intensity proportional to the magnitude of the change.

Stock	CRASH_lag	DECAL_lag	SIZE_lag	SSB_lag	Volatility_lag
ACS	60.1	51.2	4.7	192.6	13.3
ACX	3.3	8.2	6.0	33.5	23.7
AENA	13.7	4.0	1.3	2.7	4.8
AMS	6.3	3.8	167.5	59.8	3.5
ANA	8.8	1.4	0.5	0.2	55.1
BBVA	30.6	408.9	223.6	65.4	14.7
BKIA	2.5	163.3	2.3	67.6	38.0
BKT	1.5	3.7	7.7	33.5	161.8
CABK	433.8	770.8	685.2	6.2	1826.1
CIE	52.6	2.7	4.4	575.9	62.8
CLNX	687.8	397.9	21.8	52.6	100.0
COL	0.0	2.6	9.1	21.5	51.1
ELE	18.5	115.1	1.3	25.9	375.3
ENG	1.9	19.2	2.2	2.2	15.7
FER	5.7	103.0	4.3	15.6	63.9
GRF	9.6	1.8	0.3	1.9	14.4
IAG	16.8	24.4	0.6	20.2	33.2
IBE	103.5	571.3	52.4	22.5	158.5
IDR	33.9	5.2	0.6	21.6	165.4
ITX	25.4	89.7	12.9	36.0	239.1
MAP	12.7	93.8	1.0	6.7	68.8
MEL	61.2	83.1	1.5	310.2	219.9
MRL	20.4	3.8	1.5	81.0	109.1
MTS	47.2	75.8	1.4	265.8	142.0
NTGY	33.6	23.4	1.4	70.7	169.5
REE	90.1	39.1	8.6	68.6	55.0
REP	22.8	9.4	27.6	5.3	102.4
SAB	3.8	157.8	6.7	27.0	3.5
SAN	16.8	78.5	82.1	53.9	90.5
SGRE	121.5	7.6	195.8	97.8	732.6
TEF	16.0	437.5	30.2	67.5	81.8
VIS	4.0	101.3	0.1	8.8	29.2

Removed confounder

Color Scale Legend
0.0
182.6
365.2
547.8
730.4
913.1
1095.7
1278.3
1460.9
1643.5
1826.1

Figure A2. Relative change (%) in the VPIN coefficient after removing individual confounders

Figure A2. Relative change (%) in the coefficient after removing individual confounders in the VPIN to SLOPE specification. The heatmap shows the percentage variation in the estimated coefficient for each IBEX-35 stock when a given confounder is removed from the model. Positive values represent an increase in the VPIN coefficient upon confounder removal, whereas negative values (if present) indicate a decrease. Values are centered at zero and visualized with a diverging "coolwarm" scale, where darker shades reflect larger absolute change.

Appendix B. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.mulfin.2025.100944.

Data availability

The authors do not have permission to share data.

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